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1 Introduction

1.1 Overview of the Thesis

Over the last decades, the U.S. labor market has changed significantly. These developments can not only be attributed to cyclical components influencing labor market conditions during economic downturns but also partly to important and slow moving structural factors. How do changing labor markets affect workers? Discussing and answering this question is an important task for researchers, not only because labor earnings are a major source of income, making up around 60 percent of household income, but also because workers spent a large part of their lifetime at work, on average 34 hours a week for 38 years of their lives.[1] I contribute to the understanding of changing labor markets by focusing on three specific aspects: technical change, selective hiring, and judicial ideology. While this thesis consists of three independent research papers, they are connected by an overarching focus on firms' hiring behavior and associated consequences for workers' employment conditions and opportunities.

Chapter 2, which is joint work with Tobias Föll, explores the effect of routine-biased technical change on both the occupational and the union-membership choice of workers and thus analyzes the connection between polarization and deunionization. Both phenomena radically changed the U.S. labor market over the last decades and have proven to be especially harmful for middle-wage workers: job market polarization because the relative shift in labor demand away from routine occupations has suppressed wage growth in that area and deunionization because unionization rates and union wage premia are typically highest among lower middle-skill workers. Borrowing the methodology from the trade (cf. Autor et al., 2013) and migration literatures (cf. Dustmann et al., 2017) and controlling for industry and occupational composition, we document that the decline in unionization rates has been significantly more pronounced in states with a larger initial employment share in routine-intensive occupations. Additionally, we show that this decline is not driven by a simple composition effect but mainly by within-industry and within-occupation changes. We argue that routine-biased technical change is not only the main driving force behind polarization but also behind declining unionization rates. To shed light on this result, we develop a joint theory of polarization and deunionization. In a search and matching model that endogenizes the occupational and the union-membership

[1] See University of Groningen and University of California, Davis, Share of Labour Compensation in GDP at Current National Prices for United States, retrieved from FRED: fred.stlouisfed.org/series/LABSHPUSA156NRUG, January 28, 2021; U.S. Bureau of Labor Statistics, Average Weekly Hours of All Employees, Total Private, retrieved from FRED: fred.stlouisfed.org/series/AWHAETP, February 3, 2021; and Skoog and Cieka (2010).

choice of workers, a polarizing labor demand structure worsens the bargaining position of unions and makes participation in collective bargaining less attractive for workers. Falling union density further amplifies employment polarization in the model.

Since the Great Recession workers in the U.S. face a significantly higher risk of becoming involuntarily part-time employed. At the same time, overall job-to-job flows have decreased dramatically. In Chapter 3, I study the connection between involuntary part-time employment, workers' job mobility, and the role of firms' hiring behavior. I document two new stylized facts about involuntary part-time employment in the U.S. First, involuntary part-time workers flow at a higher rate to new employers than workers not affected by a mismatch between actual and desired work hours. Second, while job mobility has declined for all worker types since the 1990s, involuntary part-time workers experienced the most pronounced drop in job-to-job transitions. Motivated by the literature on the negative scarring effect of unemployment (cf. Arulampalam, 2001; Eriksson and Rooth, 2014) as well as mismatch and nonstandard employment (cf. Fouarge and Muffels, 2009; Pedulla, 2016; Nunley et al., 2017; Biewen et al., 2018), I also show that this development can be related to changes in the hiring behavior of firms, in that they have become more selective over the last decades. I introduce involuntary part-time work into a search and matching model with on-the-job search, in which poaching offers of full-time firms generate an hours ladder and job opportunities are shaped by a worker's current employment status. In line with the empirical evidence presented in this chapter, involuntary part-time workers move more frequently to new jobs, since they are willing to accept a wider range of job offers for working the desired number of hours. The key mechanism in the model is the interaction between recruitment and a scarring effect of part-time work. That is, when individual employment histories matter, and firms become more selective when hiring, having worked part-time deteriorates workers' employment opportunities and leads to a reduction in the rate of finding full-time employment. The severity of this scarring effect crucially depends on the degree of selective hiring in the model.

In Chapter 4, which is joint work with Christian Bredemeier and Tobias Föll, we examine how the ideological composition of the Supreme Court affects labor market conditions for workers in the U.S. The importance of this topic has been lately emphasized by the debate over Ruth Bader Ginsburg's Supreme Court replacement by Amy Coney Barett. While Supreme Court nominations are perceived to be among the most important decisions of a U.S. president, existing evidence on the economic impact of the Supreme Court is either case-based or purely anecdotal. In this chapter, we document substantial labor market effects of judicial ideology, using an extensive dataset on court ideology, rulings, and labor market outcomes. Our identification strategy exploits variation across U.S. states in how strongly jurisprudence in a state is affected by ideological changes at the Supreme Court. Specifically, we use an interaction term between time-varying Supreme Court ideology and a time-invariant state-specific measure of the ideology of district court judges in regressions that include both time and state fixed effects. We find that an increase in the share of conservative rulings substantially increases the employment rate but decreases pay as well as other measures of job quality and increases inequality. We show that our main empirical results can be rationalized in a search and matching model with wrongful-termination lawsuits. In the model, a larger share of pro-business rulings erodes workers' bargaining power, which negatively affects workers' wages. Lower wages imply lower labor costs for firms, resulting in a larger number of posted vacancies, a higher job-finding rate and in a lower unemployment rate.

1.2 Contribution to Chapters 2, 3, and 4

Chapter 2, "A Joint Theory of Polarization and Deunionization" (Revise and Resubmit, Review of Economic Dynamics), is joint work with Tobias Föll. The chapter is based on a research idea developed by myself, which was refined and finalized in discussion with Tobias Föll. The empirical analysis was conducted by Tobias Föll and myself. I was mainly responsible for the formal representation of the labor market model and Tobias Föll for the quantitative evaluation. The first draft as well as all revisions of the paper were written by both of us.

Chapter 3, "The Role of Job-to-Job Transitions for Involuntary Part-Time Employment", is single authored and thus based on my own research.

Chapter 4, "Outlawed: Estimating the Labor Market Effects of Judicial Ideology", is joint work with Christian Bredemeier and Tobias Föll. The chapter is based on a research idea developed by Christian Bredemeier. The related literature was collected and discussed by Christian Bredemeier and Tobias Föll. I contributed the labor market data and discussion of appropriate control variables from the CPS. Furthermore, I was mainly responsible for merging the different datasets. The empirical analysis was performed by Christian Bredemeier and myself, whereas Tobias Föll developed the formal representation and quantitative evaluation of the labor market model. We all revised the first draft of the paper, which was written by Tobias Föll.

2 A Joint Theory of Polarization and Deunionization

Authors: Tobias Föll and Anna Hartmann

2.1 Introduction

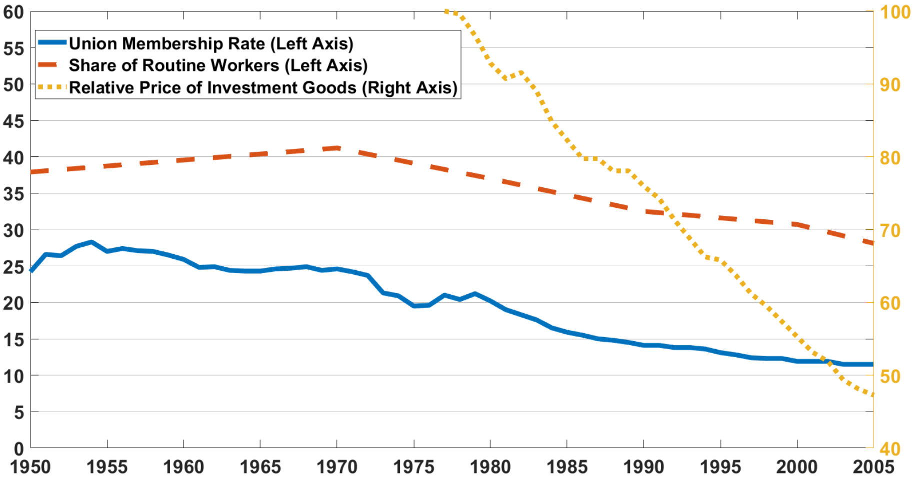
Job market polarization and deunionization have radically changed the U.S. labor market over the last decades.[1] The employment share of workers in the middle of the skill distribution has been continuously decreasing in the U.S. and is now more than 10 percentage points below its value in the 1980s (cf. Autor and Dorn, 2013), while the overall U.S. union membership rate declined from 23.0% in 1980 to 10.3% in 2019 (cf. Hirsch and Macpherson, 2003). Both phenomena have proven to be especially harmful for middle-wage workers: job market polarization because the relative shift in labor demand away from routine occupations has suppressed wage growth in that area and deunionization because unionization rates and union wage premia are typically highest among lower middle-skill workers. Accordingly, identifying and implementing suitable policies to support the middle class has become an ever more pressing issue for today's policymakers, especially considering the recent trends of political radicalization among this group (cf. Post, 2017).

Job market polarization is most commonly explained by the routinization hypothesis, which states that middle-wage workers performing mostly routine tasks are replaced by machines or computers, whereas non-routine tasks carried out by low-wage and high-wage workers are harder to automate (cf. Autor et al., 2003, 2006b; Goos et al., 2009; Autor and Dorn, 2013; Reshef, 2013; Michaels et al., 2014; Autor et al., 2015; Feng and Graetz, 2015; Caines et al., 2017; Eden and Gaggl, 2018). In contrast to job polarization, no consensus has been reached regarding the mechanisms behind deunionization (cf. Dinlersoz and Greenwood, 2016; Ortigueira, 2013; Aghion et al., 2011; Lee and Roemer, 2005). In this paper, we argue that routine-biased technical change is also the main driving force behind the falling unionization rates.[2] As a first indication, Figure 2.1 depicts the falling relative price for investment goods (as a proxy for routine-biased technical change), the employment share of workers in routine occupations, and the union

[1]Job market polarization refers to the falling employment shares in middle-skill occupations and increasing employment shares in low-skill and high-skill occupations. Deunionization describes the ongoing decline in union membership rates.

[2]The literature on technical change and deunionization is discussed in Section 2.2.

Figure 2.1. Relative Price for Investment Goods, Share of Routine Workers, and U.S. Union Membership Rate



Note: The share of workers in routine occupations is constructed using the dataset and the occupational classification by Autor and Dorn (2013). Data for the union membership rates are taken from Mayer (2004), who merges data from the Current Population Survey, the Union Membership and Coverage Database constructed by Hirsch and Macpherson (2003), and from the Bureau of Labor Statistics Handbook and Employment and Earnings Survey. The membership rate includes all wage and salary workers. Public sector and agricultural workers are included in order for the data to be comparable to the data used in Autor and Dorn (2013). Missing data points are extrapolated from adjoining data points. The FRED series for the relative price of investment goods is measured as the investment deflator divided by the consumption deflator and displayed as an index with $1980 = 100$. We display the relative price for investment goods rather than the price for computer capital since data on the former is more reliable and available for a longer time period.

membership rate for the U.S. between 1950 and 2005. The union membership rate and the share of routine workers display a very similar negative trend over the last decades (with a correlation of 0.92).

To estimate the effect of routine-biased technical change on unionization, we borrow methodology from the trade (cf. Autor et al., 2013) and migration literatures (cf. Dustmann et al., 2017). Specifically, we use an interaction term between time-varying relative prices for investment goods and time-invariant state-specific routine employment shares in regressions of unionization rates that include both time and state fixed effects. Using state-level labor market data, we document that the effect of falling prices for investment goods on unionization rates is more pronounced in U.S. states with a larger share of workers employed in routine-intensive occupations, indicating that states that are more strongly affected by routine-biased technical change also experience larger declines in unionization rates. Additionally, and in contrast to conventional wisdom, we illustrate that the decrease in union membership is not mainly driven by changes in the industry or occupational composition.

Motivated by this, we develop a joint theory of polarization and deunionization. We endogenize both the occupational choice of workers, who differ with respect to their ability, and the union status of a firm in a search and matching model of the labor market. The occupational choice is modeled by giving previous routine workers the option to switch to low-skill manual occupations upon becoming unemployed. The union status of a firm is determined through an election, in which the employees decide whether they want to form a union, and consequently a collective bargaining unit, or whether they want to bargain individually over their wages.[3]

The main mechanism behind our results is quite simple. Relative prices for computer capital, which is able to replace routine tasks, fall (proxying for routine-biased technical change).[4] This reduces the demand for routine workers, whereas manual and abstract workers, who are complementary to routine tasks, are in greater demand. The change in the labor demand structure implies that wages in manual occupations increase by more than wages in routine occupations. Manual workers, who benefit from the changing demand structure, are discouraged from voting in favor of a collective bargaining agreement because the lower demand for routine workers dampens the growth of union wages. The lowest-skilled previously unionized routine workers, when faced with lower wages compared to manual workers, decide to switch occupations. This amplifies the initial polarization caused by routine-biased technical change.

We assess quantitatively the effect of routine-biased technical change on occupational decisions and on union formation. The model is calibrated to match U.S. data for the time period between 1983 and 2005. Predicted changes in the employment and wage distribution are close to the data. Additionally, routine-biased technical change, through changes in the labor demand structure, leads to a drop of 9.3 percentage points in overall union density in the model compared to a drop of 6.6 percentage points in the data. The falling union density amplifies polarization: as previously unionized routine workers are more likely to switch occupations when they are unable to find a routine job that is covered by a collective bargaining agreement, about 15% of the simulated changes in low- and middle-skilled employment are driven by deunionization.

The remainder of the paper is organized as follows. Previous research on technical change and deunionization is discussed in Section 2.2. Empirical evidence on job market polarization and deunionization is presented in Section 2.3. We give an overview of the union framework in the U.S. in Section 2.4. The model and analytical results are presented in Section 2.5. In Section 2.6 we provide a quantitative evaluation of the model. Policy implications are discussed in Section 2.7. To conclude, the results of this paper are summarized in Section 2.8.

[3] A bargaining unit is commonly defined as a group of employees that shares a set of interests and may reasonably be represented by a collective bargaining agreement.

[4] Technically speaking, our results on deunionization only rely on the (observed) drop in relative prices for computer capital. Any development triggering this drop generates polarization and deunionization in our model. The extensive literature on polarization has singled out routine-biased technical change as the most likely cause (cf. Goos et al., 2009). Additionally, other potential explanatory factors, like international trade, arguably affect workers in manufacturing industries directly, whereas workers in other industries are mainly affected through composition effects (cf. Baldwin, 2003). However, the decomposition analysis in Section 2.3 clearly indicates that deunionization is mainly driven by within-industry and within-occupation changes. Furthermore, the analytical evaluation of the model in Section 2.5.7 reveals that other explanatory factors also imply far less pronounced changes in unionization rates.

2.2 Related Literature

This paper contributes to the literature on job polarization, the literature on deunionization and especially to the small macro-theoretical literature that studies the relationship between technical change and unionization. Going beyond CPS data, Farber et al. (2018) analyze new micro-data on unionization and provide two major empirical observations against which the predictions of macro-theoretical models of deunionization can be tested. First, the unionization rates of high-skilled workers has remained surprisingly constant over the last eighty years while the large changes have mainly been driven by increasing or decreasing membership among low- to middle-skilled workers. Consequently, the relative skill level of union vs. non-union members has increased since 1970. Second, despite large changes in unionization rates the average union wage premium has remained relatively constant. Both observations are supported by the literature. First, several empirical studies, including DiNardo et al. (1996) and Rueda et al. (2002), document that unions have become less effective in redistributing earnings over the last decades. This argument is taken up and extended in Baccaro and Locke (1998) and Checchi et al. (2010), who both highlight disillusion about potential wage growth as the driving force behind the sharp decline in union membership rates among the least skilled workers. Second, Bryson (2002), Hirsch and Schumacher (2004), and Breda (2015) all provide evidence for relatively constant union wage premia.

2.2.1 Skill-Biased Technical Change and Deunionization

It is straightforward to see that a canonical model of skill-biased technical change and deunionization is at odds with both of these observations. Consider the canonical model by Acemoglu et al. (2001) in which the economy is populated by low- and high-skill workers. Unions, which are comprised of both types of workers, aim at extracting more equal and on average higher wages for its members. Skill-biased technical change increases the skill premium in the model and therefore the outside option for high-skilled union members who decide to opt out of the bargaining unit. Union members become less skilled on average which decreases their value for firms and leads to lower union wage premia.

Açıkgöz and Kaymak (2014) study deunionization in a search and matching framework with endogenous union membership. In their model, an exogenous increase in the skill premium encourages the most skilled workers to leave the union, while firms avoid to hire the least skilled union workers. The drop in unionization rates at the top of the wage distribiution is as large as the drop at the bottom of the skill distribution, leaving the skill ratio of union to non-union members unchanged. At the same time, the large reduction in the unionization rate of high-skilled workers reduces the average union wage premium.

Dinlersoz and Greenwood (2016) analyze a general equilibrium model of unionization with heterogeneous firms, skilled, and unskilled labor. The model has nothing to say on union membership rates for high-skilled workers as these are excluded from unionization by assumption.

When unskilled labor exhibit a relative high productivity, unions decide to organize many firms and calling for high wages for their members. An increase in the skill premium due to skill-biased technical change thus leads to sharply declining union wage premia.

2.2.2 Routine-Biased Technical Change and Deunionization

In contrast to models of skill-biased technical change, our model of routine-biased technical change is consistent with both empirical observations. First, as manual workers benefit from the changing demand structure, their incentives to vote for a collective bargaining agreement decrease sharply, leading to a large drop in the membership rates of low- to middle-skilled workers. The voting decision of high-skilled workers, who are, based on the union structure in the U.S., see Section 2.4, organized in a separate union, is only mildly effected by routine-biased technical change. This leads to an increase in the skill ratio of union vs. non-union members. Second, endogenous voting on firm-level unionization implies that those unions providing the lowest wage premia for their members will be terminated. This counteracts the negative effect of routine-biased technical change on union wages and generates constant average union wage premia.

2.3 Empirical Evidence

In this section we present empirical evidence on the within-industry and within-occupation contribution to deunionization and on the relationship between polarization and declining union membership rates. We analyze both cross-country and state-level data.

2.3.1 A Decomposition Analysis

Conventional wisdom holds that the decline in unionization rates since the 1980s is mainly driven by a composition effect: employment in the heavily unionized routine-manufacturing occupations decreases while employment in the less-unionized service and information technology occupations increases. In this section, we illustrate that changing employment shares between industries and between occupations actually contributed only little to declining union membership rates between 1983 and 2005, which are mainly driven by strong within-industry and within-occupation declines in unionization.

Borrowing methodology used in, among others, Farber and Krueger (1992) and Baldwin (2003), we conduct a decomposition exercise to assess the relative importance of within- and between-industry and within- and between-occupation changes for deunionization. The within-industry (within-occupation) component measures the effect of a change in the union membership rate for a specific industry (occupational group), keeping the employment share in that industry (occupational group) constant. The between-industry (between-occupation) component measures the effect of a change in the employment share of a specific industry

Table 2.1. Changing Unionization Rates - Decomposition, 1983 – 2005

Industry	Percentage point	Share
Total change	-9.18	100%
Within-industry	-8.70	94.87%
Between-industry	-0.48	5.13%

Occupation	Percentage point	Share
Total change	-11.01	100%
Within-occupation	-8.93	81.07%
Between-occupation	-2.08	18.93%

Note: Data for industry employment shares, occupational employment shares and union membership rates are taken from Hirsch and Macpherson (2003). Industries include mining, construction, manufacturing, transportation, trade, services, finance, insurance, real estate, and public administration. Occupational groups include executive, managerial, professional, sales, machine operating, construction, transportation, and service. Due to different samples and missing observations the total change calculated using union membership rates by industry and by occupation is not identical.

(occupational group), keeping the union membership rate in that industry (occupational group) constant. Summing up both components over all industries (occupational groups) yields the estimated overall change in the union membership rate.

For the analysis, we use data on industry-specific and data on occupation-specific union membership rates for several industries and occupational groups provided in the Union Membership and Coverage Database described in Hirsch and Macpherson (2003). The results are summarized in Table 2.1. Nearly 95% of the decline in unionization rates is accounted for by the within-industry component, with changing industry employment shares only contributing about 5%. These results are in line with previous empirical findings (cf. Baldwin, 2003). A similar picture emerges for the within- and between-occupation contribution to deunionization. Over 80% of the overall decline in unionization rates is driven by within-occupation declines in membership rates with between-occupation changes accounting for less than 20%. When the occupational groups are reduced to abstract, routine, and manual, using the classification by Autor and Dorn (2013), the contribution of the between-occupation component drops further to below 5%. Thus, contrary to conventional wisdom, deunionization is mainly driven by within-industry and within-occupation changes in union membership rates and not by simple composition effects.

This analysis is also informative about routine-biased technical change as the potential driving force behind deunionization. In contrast to other explanatory factors, routine-biased technical change is consistent with the observation of deunionization being mainly driven by within-industry and within-occupation changes in unionization rates, see Section 2.6. International trade, for example, directly affects workers in manufacturing industries, whereas workers in other industries are mainly affected through composition effects (cf. Baldwin, 2003).

2.3.2 Linking Polarization and Deunionization

A first look at the detailed statistics on union creation and union termination in the 20th century in Troy and Sheflin (1985) reveals that 1970 has been the year with the highest number of newly founded unions, while the most union terminations are observed in 1980. The accelerated decline in union membership rates in the late 1970s to early 1980s fits well with the documented starting point of job polarization, which can be observed in the U.S. and several European countries at least since the 1980s (cf. Autor and Dorn, 2013; Goos et al., 2009).[5] Additionally, and supporting our argument, Dinlersoz and Greenwood (2016) document that the steep decline in union membership rates in the 1980s followed the emergence and diffusion of early advanced technologies.

Cross-Country Evaluation

Looking at cross-sectional evidence, the degree of unionization is more pronounced in countries with larger degrees of job and wage polarization (cf. Meyer, 2019; von Brasch et al., 2018). This does not only hold for the comparison between the U.S. and Europe, but also within the group of European countries. The Nordic countries, which experienced upgrading rather than polarization, exhibit constant or even increasing union membership rates.[6]

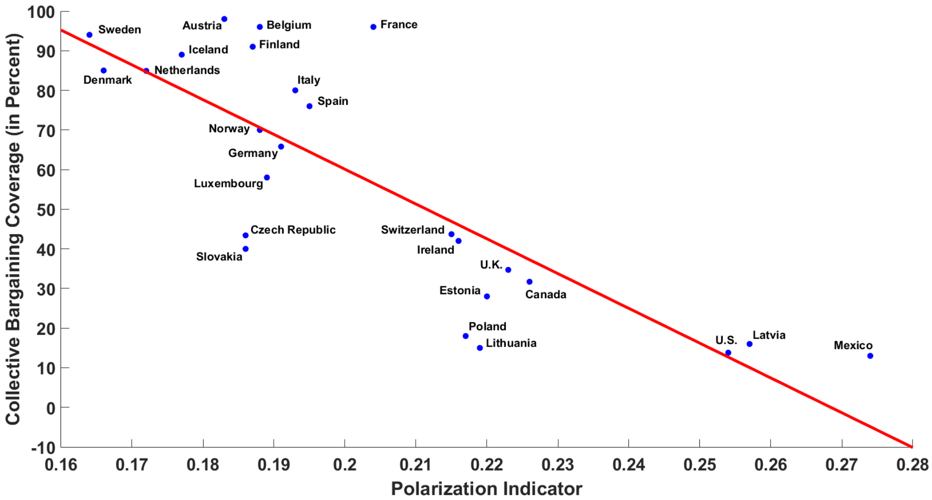
Figure 2.2 plots the polarization indicator developed in Duclos et al. (2004), which evaluates the distance between and the distinction of income groups, against the collective bargaining coverage for the U.S., Canada, Mexico, and several European countries.[7] Despite the small sample size, the negative coefficient in an OLS regression of the collective bargaining coverage on the polarization indicator is statistically significant at the 0.1%-level.

[5] The small decline in union membership rates in the late 1950s is usually explained by political resistance and the sharp increase in labor force participation of women, who tend to be less unionized (cf. Oh, 1989; Troy and Sheflin, 1985).

[6] The term upgrading refers to a specific pattern of changes in the employment structure, where employment growth is positively correlated with the required skill level.

[7] In contrast to the U.S., the differences between union membership rates and the percentage of workers covered by a collective bargaining agreement are large for most of the European countries. Thus, when looking at union influence, the share of workers covered by a collective bargaining agreement seems to be more appropriate here. The results also hold when exchanging the collective bargaining coverage for union density. The results are very similar when using changes in collective bargaining coverage instead of collective bargaining coverage.

Figure 2.2. Polarization and Collective Bargaining Coverage across Countries, 2004



Note: Figure 2.2 plots the polarization indicator developed in Duclos et al. (2004) against the collective bargaining coverage for the U.S., Canada, Mexico, and several European countries. Country selection is based on data availability. For all countries the polarization indicator is calculated for the year 2004. The collective bargaining coverage is the share of employed workers covered by a collective bargaining agreement in 2004 from the OECD data. The red line is the result of an OLS regression of the polarization indicator on the collective bargaining coverage. The regression coefficient is $\beta = -8.78$ and R^2 is 0.66.

Polarization and Deunionization Across U.S. States

Due to vast differences in the institutional frameworks of the considered countries and due to the small number of countries for which reliable estimates can be obtained for the entire sample period, the previous results are merely suggestive of a relationship between polarization and deunionization. Using broad state-level labor market data for the U.S., we aim to establish a causal link between the two phenomena. To isolate the part of the change in state-level unionization rates that is driven by a nation wide development (and therefore arguably exogenous to local labor market conditions), i.e. falling prices for computer capital, we use an interaction term between the time-invariant initial routine employment share in a state and the time-variant relative price of investment goods in regressions with state-level unionization rates as the dependent variable.

Data Sources We use labor market data from the Current Population Survey (CPS). Data on union membership and union coverage is taken from the CPS and the Union Membership and Coverage Database constructed by Hirsch and Macpherson (2003) using CPS data. For capital prices we use the relative price of investment goods, which is calculated as the investment deflator divided by the consumption deflator. For minimum wage laws we use the minimum wage rates by state. Both series are taken from Federal Reserve Economic Data (FRED). Data on the federal intergovernmental revenue is taken from the State and Local Government Finance Dataset constructed by the Census Bureau. The tax burden is constructed by the Tax Foundation and calculated as the total amount of paid taxes divided by the state's total income. Data on state legislatures is obtained through the State Partisan Composition collected by the National Conference of State Legislatures.

Sample Selection We choose 1983 as the starting date for our analysis, as union membership estimates by detailed occupation are provided in the Union Membership and Coverage Database from this date onwards. 2005 is chosen as the endpoint because Beaudry et al. (2016) document a reversal in the demand for cognitive skills since the early 2000s and accounting for this reversal goes beyond the scope of our analysis.

An observation is a state-year combination, as union membership rates and detailed labor market data can only be constructed at the state level from the CPS. In principle, our sample thus contains 23 years × 50 states = 1150 state-year observations.[8] After excluding observations for which we lack information on certain control variables, we are left with a consistent sample of 1116 observations.

Methodology We estimate

$$u_{s,t} = \gamma \cdot p_{K,t} \cdot rsh_{s,83} + \beta \cdot X_{s,t} + \delta_s + \eta_t + \varepsilon_{s,t}, \tag{2.1}$$

where $u_{s,t}$ is the union membership rate or union coverage rate in state s in year t, $p_{K,t}$ is the relative price of investment goods in year t, and $rsh_{s,83}$ is the employment share in routine-intensive occupations in state s in year 1983.[9] $X_{s,t}$ is a vector of control variables, including controls for state policy (minimum wage laws, tax burden), state legislation (party of governor, majority party in state senate and state house), state demographics (age, education, gender, ethnic composition), industry composition, and occupational composition.[10] The complete list of control variables is provided in A.7. δ_s and η_t are state and time fixed effects and $\varepsilon_{s,t}$ is the residual. Observations are weighted by the average state population over our sample period.

We explicitely address two potential concerns about our methodology. First, the effect of routine-biased technical change might work through changes in employment composition. To adress this concern, we run seperate regressions with and without controls for the industy and occupational composition in a state. Comparing these regressions allows us to gauge the relative importance of composition effects. Second, standard errors are not clustered as our regressions include state fixed effects and there is no reason to expect heterogeneity in the sampling or in the treatment effects (cf. Abadie et al., 2017).

Results In a first step, we confirm that the negative relationship between the initial employment share in routine-intensive occupations and the subsequent change in the share of

[8] The District of Columbia is excluded because of its specific labor market structure.

[9] Occupations are classified using the classification in Autor and Dorn (2013).

[10] The state legislature in Nebraska is unicameral and officially non-partisan. However, since there has been a de facto Republican majority from 1983 to 2005, independent of how Nebraska is treated, effects of this specific state legislature will be absorbed by the state fixed effect.

Table 2.2. Regression Results for Changes in the Routine Employment Share

	(1)	(2)	(3)	(4)
Initial routine employment share	-0.8430***	-0.8174***	-0.6639***	-0.7881***
	(0.1029)	(0.0845)	(0.2267)	(0.0896)
Observations	50	50	50	50
R^2	0.8960	0.8648	0.8306	0.6174
Industry and occupation controls	yes	yes	no	no
State policy controls	yes	no	yes	no
State legislation controls	yes	no	yes	no
State demographic controls	yes	no	yes	no

Note: Observations are weighted by the average state population over our sample period. The standard errors are reported in parentheses. *** indicates significance at the 1 percent level, ** indicates significance at the 5 percent level, and * indicates significance at the 10 percent level.

routine-intensive occupations documented for U.S. commuting zones by Autor and Dorn (2013) holds on the state-level as well. This allows us to use the initial routine employment share in a state as an instrument for changes in the routine employment share, which adresses potential endogeneity concerns.

Column (1) in Table 2.2 reports the results for our most preferred specification, including the entire set of controls. The other three columns illustrate that the results do not depend on the specific set of controls. In all four columns, as in Autor and Dorn (2013), the initial routine employment share in 1983 is highly predictive of the change in the routine employment share between 1983 and 2005. States with a higher initial routine employment share are the ones that experience more pronounced employment polarization.

In a second step, we use the interaction term between the time-invariant initial routine employment share and the time-variant relative price of investment goods in regressions with state-level unionization rates as the dependent variable.[11] As we have shown that states with a larger initial employment share in routine-intensive occupations are more strongly affected by routine-biased technical change in a first step, a positive coefficient on the interaction term would indicate that routine-biased technical change (measured as the relative price of investment goods) triggers declining unionization rates.

[11] Several robustness checks are discussed in A.6.

Table 2.3. Regression Results for Unionization Rates

	(1)	(2)	(3)	(4)
Capital prices	0.3104***	0.4267***	0.2914***	0.3588***
× routine employment share	(0.0509)	(0.0516)	(0.0465)	(0.0459)
Observations	1116	1116	1116	1116
R^2	0.9870	0.9833	0.9864	0.9819
Industry and occupation controls	yes	yes	no	no
State policy controls	yes	no	yes	no
State legislation controls	yes	no	yes	
State demographic controls	yes	no	yes	
Year fixed effects	yes	yes	yes	yes
State fixed effects	yes	yes	yes	yes

Note: Observations are weighted by the average state population over our sample period. The standard errors are reported in parentheses. *** indicates significance at the 1 percent level, ** indicates significance at the 5 percent level, and * indicates significance at the 10 percent level.

The results are reported in Table 2.3. Column (1) constitutes our most preferred specification, featuring the full set of control variables. Column (2) excludes all control variables except the industry and occupation controls, Column (3) excludes only industry and occupation controls, and Column (4) excludes all control variables. The coefficient on the interaction term is positive and highly statistically significant in all four specifications. This implies that following a decrease in capital prices, the fall in unionization rates is more pronounced in states with a larger initial routine employment share.

Quantitatively, the relative price of investment goods has dropped by 48% between 1983 and 2005. Consider two states that differ by ten percentage points in their routine employment share in 1983 (this is roughly equivalent to the difference between Nevada and Alabama). When capital prices fall by 48%, our analysis suggests that the drop in the unionization rate will be about 1.5 percentage points larger in the state with the higher share of routine workers in 1983, controlling for both industry and occupational composition.

Columns (2) to (4), which leave out control variables, illustrate that our results do not depend on the specific set of controls. Specifically, the exclusion of industry and occupation controls in Column (3) does not substantially change the size of the coefficient. Thus, supporting our decomposition analysis, the regressions indicate that the effect of routine-biased technical change on unionization rates across U.S. states is mainly driven by changes within industries and within occupations.

2.4 Unions in the U.S.

In this section, we provide a brief overview of how labor unions work in the U.S. These institutional features will be used when setting up the model.

Collective bargaining in the U.S. is characterized by a high degree of decentralization with the estimated number of separate collective bargaining agreements ranging between 170,000 and 190,000 according to the Bureau of Labor Statistics. Thus, collective bargaining is mostly located at the individual firm (cf. Traxler, 1994; Katz and Lipsky, 1998; Nickell and Layard, 1999). The competence to negotiate on behalf of all workers in a so called *bargaining unit* is assigned to the union via a representation election. To constitute an appropriate bargaining unit, according to the National Labor Relations Act (NLRA), a group of employees has to share a sufficient "community of interest". According to the National Labor Relations Board (NLRB), professional employees who perform predominantly intellectual and not routine mental, manual, or mechanical work as well as supervisors and managerial employees are thus in principal excluded from bargaining units with manual and routine workers.

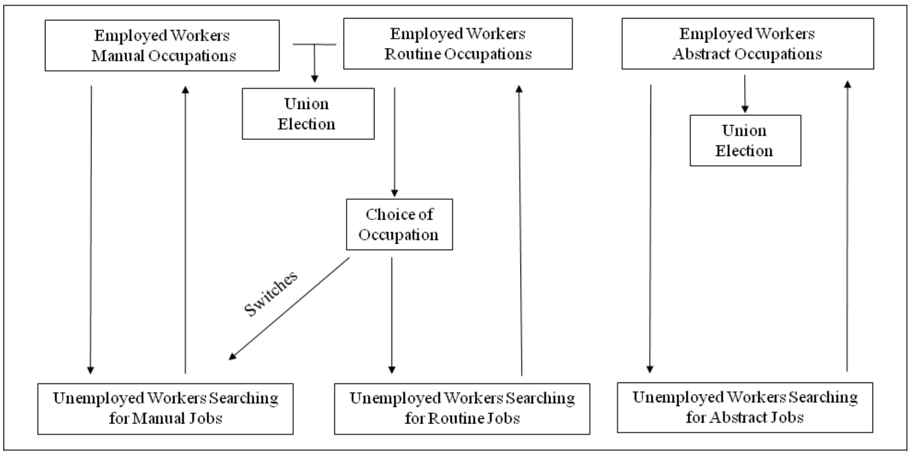
The NLRA defines all necessary steps, consisting of petitions and elections, to establish union organization and certification in a bargaining unit. The main objective of this process is to determine if a majority of workers wants to be covered by a collective bargaining agreement. Upon certification, the union exclusively represents all workers in the bargaining unit, whether they are union members or not. In the event of a lawfully-called strike, unions are allowed under the NLRA to fine members that still decide to work. If a majority of the bargaining unit votes against the union, workers are not covered by a collective bargaining agreement, independently of the individual voting decision.

With regard to the relative importance of union types in the U.S., Oh (1989) documents a declining significance of craft unionism, in contrast to an increasing prevalence of industrial unions. While the former covers mostly workers performing a specific craft (consisting of workers of a specific skill group), the latter seeks to cover all workers in a particular industry (consisting of workers of different skill groups). While high-skilled workers are predominantly organized in craft unions and low-skilled workers in industrial unions.

2.5 A Model of Occupational Decisions and Union Formation

In this section, we introduce labor unions into the multi-sectoral search and matching model developed by Albertini et al. (2017). There are two types of workers, abstract and non-abstract.

Figure 2.3. Graphical Representation of the Model



Non-abstract workers are heterogeneous and differ with respect to their ability η, which is uniformly distributed. For each ability level, there is a continuum of workers. Abstract workers are assumed to be homogenous. As depicted in Figure 2.3, workers can be specialized in manual, routine, or abstract tasks. Upon becoming unemployed, workers previously employed in routine tasks can choose to switch occupations and search in the unemployment pool of manual workers.[12]

In our model, workers' voting decision endogenously determines if a bargaining unit is represented by a union.[13] When a simple majority of the respective bargaining unit votes in favor of a union, collective wage bargaining takes place between the union and the respective firm. The collective bargaining agreement covers all workers in the bargaining unit regardless of the individual voting decision.

2.5.1 Labor Market Frictions

Search on the labor market is subjet to frictions in the sense of Mortensen and Pissarides (1994). We follow Albertini et al. (2017) and assume direct search. Thus, there is a labor sub-market for each of the three occupations $i = a, r, m$, where a, r, and m refer to abstract, routine, and

[12] To ease notation, and in line with the empirical evidence in Smith (2013), we abstract from other switches. Thus, in our model there will be 'overqualified' routine workers in manual occupations but we rule out the case of 'underqualified' manual workers in routine occupations and 'underqualified' routine workers in abstract occupations. Neither the results on deunionization nor the results on polarization depend on the assumption that manual workers are unable to switch to routine occupations. Note that because of falling prices for computer capital, the relative demand for manual workers increases. Thus, switches from manual to routine occupations only occur whenever the job-finding rate for routine workers is larger than the job-finding rate for manual workers in a unionized environment. These inefficient switches would only increase the speed at which deunionization occurs. Additionally, Smith (2013) provides evidence for the increase in abstract employment being mainly driven by increased educational attainment and not by occupational switches. Thus, we let the labor supply of abstract workers increase exogenously in our model.

[13] Our production function features constant returns to scale. In contrast to Taschereau-Dumouchel (2017), firms have no incentive to overhire high-wage and low-wage workers and to underhire middle-wage workers in our model.

manual occupations, respectively. On each sub-market, vacancies and unemployed workers are matched randomly in any period and firms learn about the ability level of a worker upon matching. Given the number of vacancies v_i posted and the share of unemployed workers u_i for every occupation i, the number of matches is determined by the following Cobb-Douglas matching technology with matching efficiency Ψ_i

$$m_i = \Psi_i v_i^{\psi} u_i^{1-\psi} \text{ where } 0 < \psi < 1 \text{ and } i = a, r, m.$$

Following Petrongolo (2001), constant returns to scale are assumed. The job-filling rate is given by $q_i = \frac{m_i}{v_i}$ and the job finding rate is given by $f_i = \frac{m_i}{u_i}$. Labor market tightness θ is defined as $\theta_i \equiv \frac{v_i}{u_i}$. When the labor market is tight, many firms compete for few unemployed workers. The job finding probability is high, but the job filling rate is low.

2.5.2 Occupational Choice

Workers can be employed in an abstract, a routine, or a manual occupation. Existing worker-firm matches are destroyed at the exogenous rates s_i, with $i = a, r, m$. The value function for unionized (superscript u) manual workers is given by

$$W_m^u(\eta) = w_m^u(\eta) + \beta[(1 - s_m)\big(\mathbb{1}_{u,+1} W_{m,+1}^u(\eta) + (1 - \mathbb{1}_{u,+1}) W_{m,+1}^n(\eta)\big) + s_m U_{m,+1}(\eta)],$$

where β is the discount factor and $w_m^u(\eta)$ denotes the union wage received by a manual union worker with ability η. $\mathbb{1}_u$ is an indicator function with $\mathbb{1}_u = 1$ if and only if the worker is a union member. Thus, the term $\mathbb{1}_{u,+1}$ indicates whether a worker in the firm is covered by a collective bargaining regime in the next period.

In turn, the non-union (superscript n) manual workers' value function is given by

$$W_m^n(\eta) = w_m^n(\eta) + \beta[(1 - s_m)\big(\big(\mathbb{1}_{u,+1} W_{m,+1}^u(\eta) + (1 - \mathbb{1}_{u,+1}) W_{m,+1}^n(\eta)\big) + s_m U_{m,+1}(\eta)],$$

where $w_m^n(\eta)$ is the wage received by a manual non-union worker with ability η.

When unemployed, workers lose their union membership.[14] Therefore, the union and non-union value functions for an unemployed manual worker are identical and given by

$$U_m(\eta) = z_m(\eta) + \beta[(1 - f_m) U_{m,+1} + f_m\big(\mathbb{1}_{u,+1} W_{m,+1}^u(\eta) + (1 - \mathbb{1}_{u,+1}) W_{m,+1}^n(\eta)\big)],$$

where $z_m(\eta)$ denotes the unemployment benefits received from the government by a manual worker with ability η.

[14] This is in line with Lewis (1989), who finds that unions are not perceived to represent the interests of the unemployed.

Analogously, the value functions for abstract workers and routine workers are

$$\begin{aligned}
W_a^u &= w_a^u + \beta[(1-s_a)\big(\mathbb{1}_{u,+1}W_{a,+1}^u + (1-\mathbb{1}_{u,+1})W_{a,+1}^n\big) + s_a U_{a,+1}],\\
W_a^n &= w_a^n + \beta[(1-s_a)\big(\mathbb{1}_{u,+1}W_{a,+1}^u + (1-\mathbb{1}_{u,+1})W_{a,+1}^n\big) + s_a U_{a,+1}],\\
U_a &= z_a + \beta[(1-f_a)U_{a,+1} + f_a\big(\mathbb{1}_{u,+1}W_{a,+1}^u + (1-\mathbb{1}_{u,+1})W_{a,+1}^n\big)]
\end{aligned}$$

and

$$\begin{aligned}
W_r^u(\eta) &= w_r^u(\eta) + \beta\left[(1-s_r)\big(\mathbb{1}_{u,+1}W_{r,+1}^u(\eta) + (1-\mathbb{1}_{u,+1})W_{r,+1}^n(\eta)\big)\right]\\
&\quad + \beta s_r \max\{U_{m,+1}(\eta), U_{r,+1}(\eta)\},\\
W_r^n(\eta) &= w_r^n(\eta) + \beta\left[(1-s_r)\big(\mathbb{1}_{u,+1}W_{r,+1}^u(\eta) + (1-\mathbb{1}_{u,+1})W_{r,+1}^n(\eta)\big)\right]\\
&\quad + \beta s_r \max\{U_{r,+1}(\eta), U_{m,+1}(\eta)\},\\
U_r(\eta) &= z_r(\eta) + \beta[(1-f_r)\max\{U_{m,+1}(\eta), U_{r,+1}(\eta)\} + f_r\big(\mathbb{1}_{u,+1}W_{r,+1}^u(\eta)\\
&\quad + (1-\mathbb{1}_{u,+1})W_{r,+1}^n(\eta)\big)].
\end{aligned}$$

The term $\max\{U_{m,+1}(\eta), U_{r,+1}(\eta)\}$ determines the occupational choice of unemployed formerly routine workers and thus identifies in which unemployment pool to search. Whenever the value of being an unemployed manual worker is larger than the value of being an unemployed routine worker, the worker switches occupations. Thus, the equation defining the endogenous occupational threshold between manual and routine occupations, η_m, is given by

$$U_r(\eta_m) = U_m(\eta_m). \tag{2.2}$$

2.5.3 Firms

The model features a continuum of final good firms and intermediate firms. As the setup admits the presence of a representative firm on each level, firm indices are dropped. To further ease notation, we only use indices related to the union status of a firm when they are necessary to understand the model mechanics.

The final good-producing firm uses three homogeneous intermediate goods, Z_a, Z_r, and Z_m, as input factors to produce the final product Y. Intermediate goods are acquired at their competitive factor prices, p_{Z_a}, p_{Z_r}, and p_{Z_m}.[15] Z_a is produced with abstract jobs L^a, Z_r with computer technology K and routine workers $L^r(\eta)$, and Z_m with manual jobs $L^m(\eta)$. Routine workers and computer technology K are close substitutes, whereas abstract workers are complementary to the intermediate good Z_r. The maximization problem of the final

[15]This production structure is chosen in order to facilitate representation, as it allows for solving the maximization problems of the good-producing firm and the intermediate firms consecutively. The job-creation conditions are identical if we instead assume that the good-producing firm directly uses manual, routine, and abstract workers as input factors.

goods-producing firm is given by[16]

$$\begin{aligned}\Pi = \max_{Z_a, Z_r, Z_m} & \{Y - p_{Z_a} Z_a - p_{Z_r} Z_r - p_{Z_m} Z_m\} \\ \text{s.t. } & Y \leq [(A Z_a^{\alpha} Z_r^{1-\alpha})^{\rho} + (A_m Z_m)^{\rho}]^{1/\rho},\end{aligned}$$

where $0 < \alpha < 1$, $-\infty < \rho < 1$, A, and A_m are parameters of the production function.

Intermediate firms maximize profits by choosing the level of employment next period and the number of vacancies subject to the firm's employment evolution constraint. Vacancy posting costs are given by c_a, c_r, or c_m. The behavior of the intermediate firm in producing the intermediate good Z_a, which is paid at price p_{Z_a}, is described by

$$\Pi^{Z_a} = \max \left\{ p_{Z_a} Z_a - \mathbb{1}_u w_a^u L_a - (1 - \mathbb{1}_u)\, w_a^n L_a - c_a v_a + \beta \Pi_{+1}^{Z_a} \right\}$$

$$\begin{aligned}\text{s.t. } & Z_a \leq L_a \\ & L_{a,+1} = (1 - s_a) L_a + q_a v_a,\end{aligned}$$

where $L_{a,+1}$ denotes the total abstract workforce next period. $\mathbb{1}_u$ is again an indicator function with $\mathbb{1}_u = 1$ indicating if the workforce in the firm is covered by a collective bargaining regime.

The behavior of the firm producing the intermediate good Z_r, which is paid at price p_{Z_r}, is described by

$$\Pi^{Z_r} = \max \left\{ p_{Z_r} Z_r - p_K K - \mathbb{1}_u \int_{\eta_m}^{\bar{\eta}} w_r^u(\eta) L_r(\eta) - (1 - \mathbb{1}_u) \int_{\eta_m}^{\bar{\eta}} w_r^n(\eta) L_r(\eta) - c_r v_r + \beta \Pi_{+1}^{Z_r} \right\}$$

$$\begin{aligned}\text{s.t. } Z_r & \leq \left[\left((1 - \mu) \int_{\eta_m}^{\bar{\eta}} \eta L_r(\eta) \,\mathrm{d}\,\eta \right)^{\sigma} + (\mu K)^{\sigma} \right]^{\frac{1}{\sigma}} \\ L_{r,+1} & = (1 - s_r) L_r + q_r v_r,\end{aligned}$$

where $0 < \mu < 1$ and $-\infty < \sigma < 1$ are production parameters, $\bar{\eta}$ denotes the upper bound on the ability distribution for non-abstract workers, and η_m the endogenous ability threshold between manual and routine workers. Following Albertini et al. (2017), firms can freely choose their desired level of computer capital K at the price p_K.

The behavior of the intermediate firm in producing the intermediate good Z_m, which is paid at price p_{Z_m}, is described by

$$\Pi^{Z_m} = \max \left\{ p_{Z_m} Z_m - \mathbb{1}_u w_m^u L_m - (1 - \mathbb{1}_u)\, w_m^n L_m - c_m v_m + \beta \Pi_{+1}^{Z_m} \right\}$$

[16] A nested production function is chosen in order to allow for larger complementarity in production between abstract and routine than between routine and manual tasks.

$$\text{s.t. } Z_m \leq L_m$$
$$L_{m,+1} = (1 - s_m)L_m + q_m v_m.$$

As in Autor and Dorn (2013), workers in manual occupations are homogenous with respect to their productivity in performing manual tasks. This implies that wages for manual workers are constant while wages for routine workers are increasing in the skill level η. Combining this with the definition of η_m in equation (2.2), it is straightforward to see that workers with an ability level lower than η_m work in manual occupations. The first order conditions and the job-creation conditions are derived in A.1 and A.2.

2.5.4 Wage Bargaining Regimes

Since we focus on the U.S., we want our union framework to be as close as possible to the institutional framework presented in Section 2.4. Workers can decide to form a union on the level of the good-producing firm, which bargains with the firm and distributes the surplus according to a union wage schedule. After hiring of new workers has occurred, all workers in the bargaining unit decide on union representation via an election. Abstract workers are excluded from the collective bargaining unit with manual and routine workers. Thus, our model features two types of unions: one industrial union - aiming to cover workers of two different skill groups - and one craft union, covering only abstract workers. If a union is established, the collective bargaining agreement covers all workers in the bargaining unit, regardless of whether or not workers individually voted in favor of the union. The voting decision of an individual worker is endogenously determined and depends directly upon the potential union wage premium. Workers vote in favor of a union if the value of being a worker in a unionized firm is higher than the value of being a worker in a non-unionized firm

$$W_i^u(\eta) > W_i^n(\eta), \text{ with } i = a, r, m.$$

In the model, the number of voting thresholds above or below which workers in a bargaining unit vote against the union depend on the choice of the union wage schedule. The thresholds are denoted by η_l^u and $\eta_l^{u,a}$ with $l \in [1, 2, ...]$, where the superscript a denotes the union for abstract workers.

If a majority of the bargaining unit votes against a collective bargaining agreement, workers in this bargaining unit are not represented by the union and wages are negotiated individually. Union and non-union wages are both determined by generalized Nash-bargaining over the respective match surplus. However, the match surplus, and thus the basis of negotiations, differs between the two bargaining regimes: non-union workers bargain individually over their marginal product, whereas the union bargains over the total match surplus of all workers in the bargaining unit.[17]

[17] This is in line with Taschereau-Dumouchel (2017).

Individual Bargaining

If a majority of the manual and routine workers votes against a union, each worker bargains individually with the firm. Denoting a worker's individual bargaining power by $\gamma^i \in [0,1]$, leads to the following surplus sharing rule for individual bargaining

$$W_i^n(\eta) - U_i(\eta) = \frac{\gamma^i}{1-\gamma^i} J_i^n(\eta),$$
$$\text{with } i = a, r, m,$$

where $W_i^n(\eta)$ is the asset value of employment for non-union members, $U_i(\eta)$ is the value of being unemployed, and $J_i^n(\eta)$ is the value of the marginal non-union worker of type i and ability η to the firm. The resulting wage schedules are

$$w_a^n = \gamma^a p_{Z_a} + \gamma^a c_a \theta_a + (1-\gamma^a)\, z_a \tag{2.3}$$

for workers in abstract jobs,

$$w_r^n(\eta) = \gamma^r p_{Z_r} y_r(\eta) + \gamma^r c_r \theta_r + (1-\gamma^r)\, z_r(\eta) \tag{2.4}$$

for workers in routine jobs, and

$$w_m^n = \gamma^m p_{Z_m} + \gamma^m c_m \theta_m + (1-\gamma^m)\, z_m(\eta) \tag{2.5}$$

for workers in manual jobs.[18]

It follows that the wages resulting from individual bargaining for abstract, routine, and manual workers are composed of the marginal productivity of the workers in each occupation, the search returns, and the outside option.

Collective Bargaining

We consider unions which negotiate wages on behalf of all covered workers within a firm and thus bargain over the total surplus of all union members.[19] We make the following assumptions based on the union framework in the U.S. outlined in Section 2.4:

[18] See A.3 for a detailed derivation of the wage schedules.

[19] For simplicity, we model collective bargaining as period-by-period Nash-bargaining instead of assuming multi-period wage contracts. As we compare steady states in the quantitative analysis, our results are unaffected by this assumption.

Assumption 1. *All workers that are covered by a collective bargaining agreement are union members.*

Assumption 2. *The union can force all of its members to strike.*

Under these assumptions, if no agreement on wages can be reached, all members of the respective bargaining unit in the unionized firm go on a strike and the firm can only produce using the remaining workers and computer capital.

While our approach gives us the share of the total surplus extracted by the union, it does not determine workers' individual union wages, i.e. the distribution of the suplus. It is well-established in the literature that unions induce wage compression, that individual union wage premia decrease in the skill level of the worker, and that craft unions tend to negotiate higher union wage premia compared to industrial unions (cf. Card et al., 2004; Streeck, 2005). To keep the degrees of freedom in choosing the wage schedule small, we assume the simplest wage schedule that is in line with these observations: unions set a constant wage for all workers in the bargaining unit (cf. Krusell and Rudanko, 2016).[20] This accords with evidence in Fitzenberger et al. (2006), who show that unions tend to prefer wage equality over higher average wages. It follows that union wages are given by

$$w^u = S^u/(L_m + L_r) \tag{2.6}$$

and

$$w_a^u = S_a^u/L_a. \tag{2.7}$$

Industrial Union

Under collective bargaining the outside option of a union member is not the value of being unemployed, but the value of being a union member during a strike.[21] Therefore, denoting the industrial union's bargaining power by $\gamma^u \in [0,1]$, the following surplus sharing rule holds in the case of collective bargaining

$$\max_{w^u} \left(\sum_i \int_{\underline{\eta}}^{\bar{\eta}} L_i(\eta) \left[W_i^u(\eta) - W_i^{u,s}(\eta) \right] \mathrm{d}\,\eta \right)^{\gamma^u}$$
$$\left(\sum_i \left\{ p_{Z_i} Z_i - p'_{Z_i} Z'_i - \int_{\underline{\eta}}^{\bar{\eta}} L_i(\eta) w_i^u(\eta)\, \mathrm{d}\,\eta \right\} \right)^{1-\gamma^u} \quad \text{with } i = r, m,$$

[20]The evaluation in A.5 establishes that the main mechanism behind falling union membership rates in our model is robust to alternative union wage schedules.

[21]Neither our qualitative nor our quantitative results depend on this assumption, as the calibration targets for the union bargaining power would be substantially lower under the assumption that the firm loses its workforce when no agreement is reached.

where $W_i^u(\eta)$ is the asset value of employment for manual and routine union members with productivity η and $W_i^{u,s}(\eta)$ is the value of being a union member during a strike. Z_i is the production of the manual or routine intermediate good and Z_i' is the production in the manual or routine sector when workers are on a strike, which is compensated at price p'_{Z_i}.

It follows that the total surplus received by the industrial union S^u is given by[22]

$$S^u = \gamma^u \sum_i (p_{Z_i} Z_i - p'_{Z_i} Z_i') + (1-\gamma^u) \sum_i \int_{\underline{\eta}}^{\bar{\eta}} L_i(\eta) w^{u,s} \, \mathrm{d}\, \eta \qquad (2.8)$$
$$\text{with } i = r, m,$$

where $w^{u,s}$ denotes the wage received by a worker during a strike, regardless of occupation and ability. Note that the total surplus of the industrial union is a function of the productivity of all manual and routine workers, while the non-union wage is a function of the individual productivity of the respective worker.

Craft Union

Analogously, denoting the craft union's bargaining power by $\gamma_a^u \in [0,1]$, the following surplus sharing rule holds in the case of collective bargaining

$$\max_{w_a^u} \left(L_a \left[W_a^u - W_a^{u,s} \right] \right)^{\gamma^u} \left(p_{Z_a} Z_a - p'_{Z_a} Z_a' - L_a w_a^u \right)^{1-\gamma^u},$$

where W_a^u is the asset value of employment for craft union members and $W_a^{u,s}$ is the value of being a union member during a strike. Z_a is the production of the abstract intermediate good and Z_a' is the production in the abstract sector when workers are on a strike, which is compensated at price p'_{Z_a}.

Thus, the total surplus received by the craft union S_a^u is given by

$$S_a^u = \gamma_a^u (p_{Z_a} Z_a - p'_{Z_a} Z_a') + (1-\gamma^u) L_a w_a^{u,s}. \qquad (2.9)$$

2.5.5 Households, Government Expenditures, and Transfers

In the model, there is one household for each occupation and for each employment status, i.e., employed and unemployed. Households own the firm, consume the final good Y and do not save. Thus, the budget constraint for workers is given by

$$C = I$$

with $I \in \{w_a^n, w_r^n(\eta), w_r^u, w_m^n, w_m^u, z_a, z_r(\eta), z_m(\eta)\}$.

[22]See A.4 for a detailed derivation.

Since the government pays out unemployment benefits, government expenditures are given by

$$G = z_a u_a + \int_{\underline{\eta}}^{\bar{\eta}} (z_r(\eta) u_r + z_m(\eta) u_m) \, \mathrm{d}\, \eta.$$

Firms can generate profits, which are

$$\Omega = \Pi^{Z_a} + \Pi^{Z_r} + \Pi^{Z_m}.$$

Transfers to households are therefore

$$\Gamma = -G + \Omega.$$

Total consumption in the economy is then given by the sum of individual wages, individual benefits, and the transfers.[23]

2.5.6 Equilibrium

With the model completely described, we define the equilibrium.

Definition 1. *An equilibrium is defined as a set of i) firms' policy functions; ii) households' policy functions; iii) a union wage schedule; iv) prices; and v) a law of motion for the aggregate states, such that: i) for each firm the firm's policies satisfy the firms' first order conditions and the job-creation conditions; ii) for each household the households' policy functions satisfy the households' first order conditions; iii) the wage is determined through individual or collective bargaining; iv) the choices given the aggregate states clear the markets; and v) the law of motion for the exogenous aggregate states is consistent with individual decisions and with the process for computer capital prices.*

2.5.7 Effects of Routine-Biased Technical Change

It is well-established in the literature, that routine-biased technical change generates polarization in models of the labor market (cf. Autor and Dorn, 2013; Albertini et al., 2017). In our model, polarization is driven by occupational switches from previous routine workers to manual occupations. This result is formalized in Proposition 1.

Proposition 1. *Routine-biased technical change increases the incentives for previous routine workers to switch to manual occupations if* $\sigma > 0$ *and* $\sigma > (1 - \alpha)\rho$.

Proof. See A.5 for a proof of Proposition 1. □

[23] This allows us to abstract from the distribution of transfers to households. The results remain unchanged when lump-sum transfers are assumed instead.

Thus, our model features polarization, as long as σ, the elasticity of substitution between computer capital and routine labor, is large enough. Intuitively, in order for routine-biased technical change to increase the incentives for occupational switches, capital and routine tasks need to be substitutes and they need to be better substitutes than routine and manual tasks in the production of the final good.

Routine-biased technical change, by increasing the capital stock, raises the productivity of manual workers by more compared to the productivity of routine workers. This leads to higher relative wages and job-finding rates for manual workers. Thus, the incentives for previous routine workers to switch to manual occupations increase. We add to this well-known result by demonstrating that routine-biased technical change additionally leads to deunionization in our model. Proposition 2 summarizes the main mechanism.

Proposition 2. *Routine-biased technical change reduces the incentives for manual workers to vote in favor of union coverage if the intermediate good produced by abstract labor, routine labor, and computer capital is a substitute to the intermediate good produced by manual labor, i.e.* $\rho > 0$.

Proof. See A.5 for a proof of Proposition 2. □

Intuitively, falling computer capital prices imply lower marginal costs of production. This increases the demand for workers in all three occupations. However, because of the complementarity of computer capital and routine workers, there is a negative substitution effect that reduces the demand for routine workers. Their marginal productivity increases by less than the marginal productivity of manual workers. Thus, the non-union wages of manual workers increase by more than the non-union wages of routine workers. The increasing relative demand for manual workers in response to the drop in the price of computer capital increases the size of the surplus the union can extract, while the negative substitution effect on the relative demand for routine workers tends to work in the opposite direction. Since unions set identical wages for manual and routine workers, routine workers benefit from the higher relative demand for manual workers while manual workers suffer from the lower relative demand for routine workers, i.e. in the union the positive demand effect for manual workers is partially absorbed by routine workers. This directly implies that non-union wages for manual workers grow by more than union wages. Furthermore, the increase in the amount of capital used in production worsens the bargaining position of unions, as a potential strike becomes less harmful for the firm. This additionally dampens union wage growth compared to non-union wage growth. Thus, the incentives to unionize decrease unambiguously for manual workers.

Note that the mechanism we emphasize here is in line with the empirical literature on union membership decisions, which emphasizes disillusion about potential wage growth as the main driving force behind sharply declining unionization rates of low-skilled workers (cf. Baccaro and Locke, 1998; Checchi et al., 2010).

The effect of routine-biased technical change on the voting incentives for routine workers is ambiguous and depends on the larger union wage growth due to the relatively larger productivity growth of manual workers and the lower union wage growth due to the larger amount of capital. In the quantitative evaluation, the incentives for routine workers to vote in favor of a collective bargaining agreement monotonically decrease with falling computer capital prices. However, even if the incentives were to increase for the lower-skilled routine workers, manual workers would still drive deunionization, as they make up between 46% and 53% of the bargaining unit inside firms.

Additionally, the analytical evaluation in this section reveals that other explanatory factors, like increasing international trade, would have a far more moderate effect on unionization rates. While any development that triggers polarization will also generate deunionization in our model, a substantial part of the decrease in membership rates is driven by the increase in the amount of computer capitel used by firms and hence by falling relative prices for investment goods.

2.6 Quantitative Analysis

In this section, all the parameters discussed above are calibrated to match different aspects of U.S. data for 1983. In line with empirical data, we let computer capital prices fall by 48% until 2005. We use the calibrated model to quantify the effect on the occupational choice of workers and on union elections. For the simulation we choose a setting with heterogeneous unions that differ with respect to their bargaining powers γ^u and γ_a^u. We consider an economy that consists of a number N of independent islands, where each island represents a set of firms in an industry. All islands are identical except for the bargaining power of the potential union. The performance of the model is evaluated along several dimensions, especially with regard to the empirical evidence on deunionization in the U.S. We focus on steady states as we are mainly interested in the long-run effect of routine-biased technical change on the economy.

In Section 2.3, we have illustrated that deunionization is driven by within-industry changes in unionization rates. Up until now, we have not discussed whether this is also true for polarization. Empirical studies stress that both within- and between-industry components are important in explaining job polarization (cf. Heyman, 2016; Foote and Ryan, 2014; Adermon and Gustavsson, 2015). The findings in Tüzemen and Willis (2013), Breemersch et al. (2019), and Bárány and Siegel (2019) all suggest that within-industry polarization accounts for about two thirds of overall polarization while Kerr et al. (2020) even find evidence for an important role of within-firm polarization.

2.6.1 Calibration

The model is calibrated to quarterly frequency. Target values pertain to economy-wide averages. Table 2.4 lists the exact parameter values as well as the source that encourages the specific choice. We first calibrate the discount factor β to a conventional value of 0.99, which implies an annual interest rate of 4%. Next, we calibrate the labor market variables. The separation rates of manual and routine workers are set to the standard value of $s_m = s_r = 0.1$ (Shimer, 2005). Following Albertini et al. (2017), we set the separation rate of abstract workers to the lower value of $s_a = 0.05$.

The matching efficiencies are calibrated in order to match the average job-finding rate between 1983 and 2005 reported in Shimer (2005). Under this calibration the job-finding rate increases with the skill level of workers. A large literature documents no or only small effects of unionization on employment: Frandsen (2012) and Montgomery (1989) on the aggregate level, Boal and Pencavel (1994) on the industry level, and DiNardo and Lee (2004) on the firm level. Furthermore, using linked employer-employee data, Brändle and Goerke (2018) argue that negative employment effects might be caused by selection in cross-sectional studies. We take this evidence into account by calibrating the matching efficiency on unionized islands to match the same job-finding rates as on non-unionized islands.

Vacancy posting costs are chosen to correspond on average to 35% of a worker's quarterly steady state wage, which lies well in the range of values found in the literature (cf. Garín, 2015; Michaillat, 2012). For simplicity, unemployment benefits and strike pay are both set to zero.[24]

All production and skill specific parameters are set in order to match data on employment shares in 1983 (30.7% manual, 35.7% routine, and 33.6% abstract workers), as well as the abstract employment share of 40.9% in 2005. This leaves manual and routine employment shares in 2005 as untargeted moments to gauge the performance of the model. The growth rates of computer capital prices g_{p_K} and abstract labor supply $g_{L_a^S}$ are calibrated to match a drop in computer capital prices by 48% and an increase in the abstract employment share of 7.3 percentage points.

Depending on birth cohort, age group, and survey data (Census/ACS, CPS, NLSY, PSID, and SIPP), the difference in wages between high school graduates and college graduates amounts to 10%-29%. The average Mincer college wage premium – over age groups, birth cohorts, and survey data – amounted to roughly 15% to 20% in the U.S. in 1983 (cf. Ashworth and Ransom, 2019).[25] Setting the bargaining power of abstract workers to $\gamma_a^n = 0.8$ and the bargaining power of manual and routine workers to $\gamma_m^n = \gamma_r^n = 0.5$ yields a college wage premium of 17% in the model in 1983 while leaving the average worker bargaining power in the standard range between 0.4 and 0.6.[26]

The bargaining power of the potential unions is assumed to be equally distributed – on the interval between 0.51 and 1 for the potential industrial unions and on the interval between 0.88

[24]The results are robust to alternative parameter choices.

[25]Mincer college wage premium refers to a wage premium that is adjusted for observable skills using the model proposed by Mincer (1974). Typically, the Mincer wage premium is roughly half the size of the raw wage premium.

[26]The college wage premium can be calculated when assuming that the individual skill η refers to the educational attainment of otherwise identical workers. If we further assume that on average manual workers have high school education, abstract workers a college degree, and routine workers some college or an associates degree, than the college wage premium is given by the ratio of abstract to manual wages in the model.

Table 2.4. Calibrated Parameters

Symbol	Interpretation	Value	Source
β	Discount factor	0.99	Annual interest rate of 4%
s_m	Manual separation rate	0.1	Garín (2015)
s_r	Routine separation rate	0.1	Garín (2015)
s_a	Abstract separation rate	0.05	Albertini et al. (2017)
Ψ_m	Manual matching efficiency	0.25	Job-finding rate 0.56
Ψ_r	Routine matching efficiency	0.33	Job-finding rate 0.56
Ψ_a	Abstract matching efficiency	0.8	Job-finding rate 0.56
ψ	Unemployment-elasticity of matching	0.5	Petrongolo and Pissarides (2001)
c_m	Manual recruiting costs	0.3	35% of wages
c_r	Routine recruiting costs	0.3	35% of wages
c_a	Abstract recruiting costs	0.5	35% of wages
A	Productivity routine and abstract input	3.4	Occupational shares in 1983
A_m	Productivity of manual input	0.77	Occupational shares in 1983
α	Marginal return to abstract labor	0.45	Occupational shares in 1983
ρ	Production parameter	0.65	Occupational shares in 1983
σ	Production parameter	0.74	Albertini et al. (2017)
μ	Production parameter	0.5	Albertini et al. (2017)
$\underline{\eta}$	Lower bound on skill	0.48	Occupational shares in 1983
$\bar{\eta}$	Upper bound on routine skill	1.44	Occupational shares in 1983
$g_{L_a^S}$	Growth rate of abstract labor supply	0.015	Abstract employment in 2005
g_{p_K}	Growth rate of computer capital prices	-0.029	Investment prices in 2005
γ^m	Manual worker's bargaining power	0.5	Midpoint of literature values
γ^r	Routine worker's bargaining power	0.5	Midpoint of literature values
γ_a	Abstract worker's bargaining power	0.8	College wage premium 1983
γ^u	Union bargaining power	0.51–1	Non-Abstract Union Membership
γ_a^u	Craft union bargaining power	0.88–1	Abstract Union Membership

and 1 for the potential craft unions.[27] With the bargaining power of the most powerful unions set to one, a lower bound of 0.88 on the bargaining power of the unions for abstract workers matches the union membership rate of 16.6% in 1983 reported in the Union Membership and Coverage Database constructed by Hirsch and Macpherson (2003) for workers in abstract occupations. Given this calibration, a lower bound of 0.51 for industrial unions matches the overall union membership rate of 19.5% in 1983, calculated using the Union Membership and Coverage Database and the employment shares from Autor and Dorn (2013).

[27]The large differences between the union bargaining powers and the individual bargaining power of a worker are necessary because under collective bargaining workers are not lost to the firm when bargaining breaks down. If we instead assume that the firm loses its workforce when no agreement is reached, the calibration targets for the union bargaining power would be substantially lower than under individual bargaining. The reason behind this is that the union bargains over the average product of all workers in the bargaining unit, while each individual workers only bargains over his or her marginal product. The results are robust to other intervals of the bargaining power.

Table 2.5. Unionization Rates: Model versus Data

	1983		2005	
	Data	Model	Data	Model
Overall	19.5%	19.5%	12.9%	10.2%
Manual workers	24.8%	21.0%	14.5%	6.3%
Routine workers	17.7%	21.0%	10.2%	6.3%
Abstract workers	16.6%	16.6%	13.4%	15.9%

Note: Data for union membership rates by occupations are calculated using the Union Membership and Coverage Database constructed by Hirsch and Macpherson (2003) and include all wage and salary workers. We use the occupational classification by Autor and Dorn (2013). The overall union membership rate is calculated using the employment shares reported in Autor and Dorn (2013) and the union membership rates by occupation.

2.6.2 Deunionization

As capital prices fall, the unions with the lowest bargaining power fail to gain majority support in the subsequent elections and are terminated.[28] Our model performs well in generating declining union membership rates between 1983 and 2005. The predicted and actual changes are given in Table 2.5, with the only targeted values being the overall and the abstract union membership rate in 1983.

The union membership rate falls by 9.3 percentage points from 19.5% to 10.2% in the model, compared to a drop by 6.6 percentage points from 19.5% to 12.9% in the data.[29] The union membership rate for manual workers drops by 14.7 percentage points (10.3 in the data), the membership rate for routine workers by 14.7 percentage points (7.5 in the data), and the membership rate for abstract workers by 0.7 percentage points (2.5 in the data).[30]

As abstract workers are unionized in a homogenous group, the higher marginal productivity due to technical change affects union and non-union wages for these workers similarly. However, under individual bargaining the higher demand for abstract workers increases the cost

[28]This model prediction is supported by evidence in the 2004 NLRB Performance and Accountability Report. Going from 1994 to 2004, the number of filed representation petitions has dropped by 25% and the share of won elections has increased by over five percentage points.

[29]Kambourov and Manovskii (2009), Gathmann and Schönberg (2010), and Cortes and Gallipoli (2017) provide evidence for sizeable costs of job switches that increase with the distance between occupations. Accounting for these costs would decrease the number of switches, increase the share of routine workers and thus lead to a smaller decline in unionization rates in the model.

[30]The model slightly overpredicts the decline in the membership rates for manual and routine workers and underpredicts the decline in membership rates for abstract workers. Possible explanations for the former are workers that remain union members despite declining monetary incentives out of habit, due to peer pressure, because of other non-monetary membership advantages, or because switching costs are too large. The latter arises because we ignore heterogeneity among abstract workers.

Table 2.6. Simulated Changes in Unionization Rates - Decomposition, 1983 – 2005

	Percentage point	Share
Total change	-10.27	100%
Within-occupation	-9.97	97.08%
Between-occupation	-0.30	2.92%

Note: The relative contribution of the within-occupation and between-occupation component is calculated using the methodology described in Section 2.3.

Table 2.7. Simulated Union Wage Premium and Skill Ratio

	1983	2005
Union wage premium	0.6%	-0.6%
Skill ratio non-unionized workers	0.53	0.62
Skill ratio unionized workers	0.4	1.75

Note: The skill ratio in the model is defined as the ratio of abstract to non-abstract workers.

of hiring a worker in the next period. The outside option under collective bargaining, i.e., a strike of abstract workers, is associated with the same costs as before. Thus, the incentives to unionize decrease slightly for abstract workers, but by less compared to manual and routine workers.

Using the same methodology as in Section 2.3, we calculate the within-occupation and between-occupation component for the three occupations in our model. The results are summarized in Table 2.6. Deunionization does not only work entirely through changes within industries (by construction), but also mainly through changes within occupations rather than through changing employment shares: over 95% of the changes in union membership rates between 1983 and 2005 are driven by the within-occupation component in our model.

Result 1. *The relative skill level of union members increases between 1983 and 2005.*

In line with empirical evidence, the union membership rate of abstract workers decreases only slightly in our model. Consider an increase in the skill level of a worker and how this affects his or her probability of being a union member. Given the predicted changes in unionization rates between 1983 and 2005, an increase in the skill level of a worker decreased the probability of being a union member in 1983, but increases the probability of being a union member in 2005. This coincides with evidence on the effect of educational attainment on the union status of workers in Farber et al. (2018). The reason is that the union membership rate of abstract workers decreases by less compared to the union membership rates of the less-skilled manual and routine workers, both in the data and in our model. The ratio of abstract to non-abstract workers inside and outside of unions in our model is reported in Table 2.7.

Result 2. *Despite falling union membership rates, the average union wage premium stays roughly constant between 1983 and 2005.*

Estimates of the average union - non-union wage differential across workers range from close to zero (cf. Bryson, 2002; Booth and Bryan, 2004) to 25% in (cf. Hirsch and Schumacher, 2004). Recent studies by DiNardo and Lee (2004) and Frandsen (2012), who focus on employer and union election data, find only very small or even negative union wage premia on average. Additionally, Streeck (2005) argues that because of its structure, industrial unions tend to exhibit even lower wage premia on average compared to craft unions.

As our model predicts that those unions exhibiting the lowest bargaining power will be terminated, union termination in the model is associated with an increasing average union bargaining power. This counteracts the decreasing relative value of low- to middle-skilled workers for the firm and generates relatively constant average union wage premia. The evolution of the union wage premium in the model is given in Table 2.7.[31] Despite the sharp drop in the unionization rate, the average union wage premium decreases by only 1.2 percentage points in the model.

2.6.3 Polarization

As shown in Section 2.5.7, falling computer capital prices lead to employment adjustments, with the lowest-skilled routine workers deciding to switch to manual occupations upon becoming unemployed.

The employment shares of the three occupational groups in the model and in the data are given in Table 2.8. The share of manual workers increases from 30.7% to 31.1% in the data and to 31.0% in the model between 1983 and 2005, while the employment share of routine workers decreases from 35.7% to 28.0% in the data and to 27.9% in the model. Figure 2.4 displays the respective percentage point changes in the employment share for each occupation.

Employment changes are less pronounced in unionized firms: as wages for manual and routine workers grow equally, the lowest-skilled unionized routine workers have no incentive to switch to manual jobs.[32] While there is no direct evidence on the polarization of the employment structure in unionized versus non-unionized firms, our model prediction is supported by two strands of the literature. First, Calmfors et al. (2001) and Rogers and Streeck (1995) argue that in many countries the management is under the obligation to at least consult with the relevant unions over restructuring and layoff plans. In these cases union officials tend to prefer policies that favor those workers who are most likely to be union members, in order to improve their

[31] The union wage premium is calculated by comparing the union wage of all union members to their potential non-union wages.

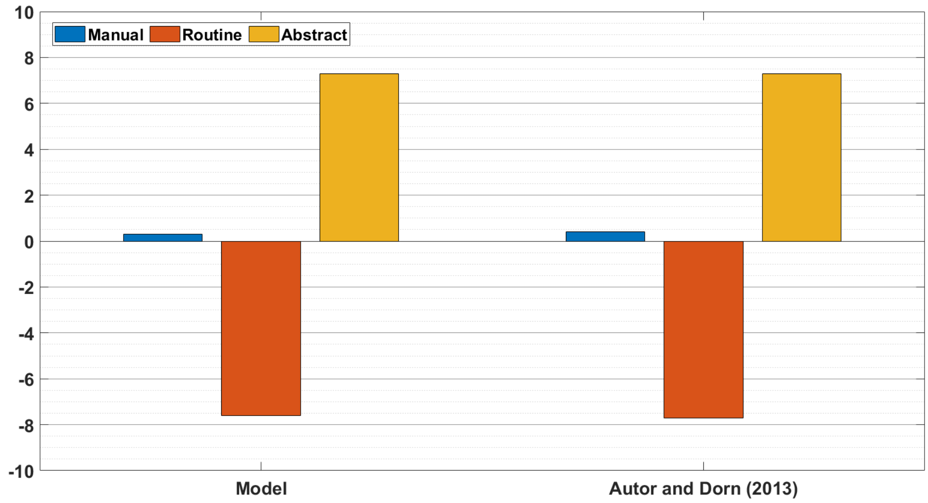
[32] This result does not depend on the specific choice of the union wage schedule but holds as long as union wages for routine workers are higher compared to union wages of manual workers.

Table 2.8. Employment Shares in 1983 and 2005: Model versus Data

	1983		2005	
	Data	Model	Data	Model
Manual	30.7%	30.7%	31.1%	31.0%
Routine	35.7%	35.7%	28.0%	27.9%
Abstract	33.6%	33.6%	40.9%	40.9%

The share of workers in each occupation is constructed using the dataset and the occupational classification by Autor and Dorn (2013).

Figure 2.4. Percentage Point Changes in Employment Shares, 1983 – 2005: Model versus Data



Note: The share of workers in each occupation is constructed using the dataset and the occupational classification by Autor and Dorn (2013).

chances in future elections. Thus, unions will likely oppose plans that reinforce polarization. Second, Connolly et al. (1986), Hirsch and Link (1987), and more recently Bradley et al. (2017) argue that unions have detrimental effects on innovation and technology adaption. As technical change is the most important driving force behind polarization, less innovation is likely to be accompanied by less polarization. This implies, as our model predicts, that deunionization amplifies polarization.

Even though the manual employment share remains roughly unchanged, there has been substantial employment reallocation with more than 10% of all routine workers in 1983 deciding to switch to manual occupations. About 15% of the occupational switches in our model are triggered by the termination of unions. When low-skilled routine workers are unable to find unionized jobs, which would pay them a substantial union wage premium, their incentives to switch occupations increase. While the model predicts routine-biased technical change to be the main explanation for job market polarization, deunionization substantially amplifies employment changes.

The changes in employment are accompanied by wage changes. The model predicts wages for abstract, routine, and manual workers to grow by 10%, 8%, and 8.5%, respectively. Although a bit smaller, these changes accord with the pattern of wage changes by skill levels reported in Autor and Dorn (2013) for the time period between 1980 and 2005.

2.6.4 Inequality

In contrast to the large effect on employment changes, deunionization has only modest effects on wage changes. Going from 1983 to 2005, the Gini index in our model increases by 18% compared to an increase of 12% for U.S. data.[33] However, since union wage premia are small on average and the unions with the lowest bargaining power are terminated, this increase in inequality is almost entirely driven by the increasing employment share of abstract workers and by their increasing relative wages. The small overall effects of deunionization on wage inequality in our model accord with the empirical findings in DiNardo et al. (1996), Frandsen (2012), and Farber et al. (2018).

The effects of deunionization for those groups that traditionally receive a high union wage premium, the lower middle-skilled workers, are substantial. The lowest-skilled previously unionized routine workers, i.e., those workers that lose their union wage premium going from 1983 to 2005 and subsequently switch occupations, are most severely affected by both polarization and by deunionization. Their wage growth would be 60% larger if they were covered by one of the remaining unions.

2.7 Discussion and Policy Implications

Our analysis has revealed that while the overall effect of deunionization on income inequality seems to be quite small, repercussions for lower middle-skilled workers are large. Implementing suitable policies to support routine workers has been in the focus of U.S. politicians long before President Barack Obama declared himself "a warrior for the middle class".[34] Taking into account evidence from Frandsen (2012), who reports that most union elections are very closely contested, even small policy changes could potentially lead to large effects on income inequality for these workers.

We briefly go through the effects of two policies that aim at supporting lower middle-skilled workers. The first policy simply abolishes union elections after the first election in 1983 and maintains the established unions regardless of worker preferences. While this approach prevents deunionization, it also prevents efficient deunionization in the sense that even unions

[33]The Gini index in our model is computed using wage ventiles.
[34]Remarks by the president on the economy, Knox College, Galesburg, IL, 24.06.2013.

generating a highly negative average wage premium would be maintained. The second policy lowers the necessary voting threshold for unions. For specific voting thresholds, this policy achieves the same results as abolishing elections, with identical downsides. However, in addition such an intervention is not well suited to stop the overall trend of declining union membership rates as the threshold would have to be regularly adjusted to changes in the economy. Furthermore, low threshold values, apart from being difficult to justify, could in principle lead to the establishment of further inefficient unions.

In our simulation, deunionization can always be prevented by adjusting the union wage schedule towards less equality inside the unionized firms. However, empirical evidence suggests that besides displaying preferences for wage equality inside the bargaining unit (cf. Fitzenberger et al., 2006), unions are also often shaped by rigid organizational structures that partly prevent them from meeting today's challenges. Waddington (2005) contends that trade union practices are perceived as formal and old-fashioned and that the representative structures inside unions are often inappropriate for the participation of all members. Bryson et al. (2016) argue that union representatives have very long tenure and tend to become less representative of the membership over their term of office.

While unionization rates decline across all age groups, according to data from the Bureau of Labor Statistics, membership rates for workers aged between 16 and 24 declined at twice the rate of overall membership between 2002 and 2012. Data on the evolution of the median age of union members points in the same direction: Dunn and Walker (2016) stress that over half of all U.S. union members are between 45 and 64 years of age. Thus, it seems that unions are mostly controlled and influenced by older members that might display a tendency to stick to established practices. Bryson et al. (2016) provide empirical evidence for the decline in union membership rates being negatively related to the degree of progressiveness of unions in a country. Thus, one straightforward policy suggestion is to restrict the tenure of union representatives to ensure that union officials are drawn from the current membership.

2.8 Conclusion

This paper explores the effect of routine-biased technical change on both the occupational and the union-membership choice of workers. We use broad state-level labor market data to illustrate that the decline in unionization rates is more pronounced in U.S. states with a larger decline in the employment share of routine-intensive occupations. We additionally show that this decline is not driven by a simple composition effect but mainly by within-industry and within-occupation changes. Building on this observation, we explore how routine-biased technical change affects both the occupational and the union-membership choice of workers. To do so, we develop a model that endogenizes both decisions in a search and matching framework.

We provide analytical results and use the calibrated model to show that routine-biased technical change, represented by a sharp drop in computer capital prices, not only generates employment and wage polarization but also deunionization. The drop in computer capital prices reduces the demand for routine workers while the demand for abstract and manual workers increases. The changing demand structure influences the surplus unions can extract and thereby also the individual union wage premium of workers. Manual workers, who benefit from the changing demand structure, are discouraged from voting in favor of a collective bargaining agreement. As wage gains for manual workers would be distributed more equally between manual and routine workers by the union, manual workers are better off bargaining individually with the firm. Former routine workers, when faced with lower wages compared to manual workers, decide to switch occupations.

We demonstrate that this effect can lead to a change in the voting outcome, with the majority of the workforce of previously unionized firms now voting against unionization and in favor of individual bargaining. In an economy in which unions differ with respect to their bargaining power, routine-biased technical change leads to a large decrease in union membership rates, as those unions exhibiting the lowest bargaining power are terminated. Since about 15% of all job switches are triggered by deunionization, this contributes substantially to employment polarization. While overall effects on income inequality are small, low- to middle-skilled previously unionized workers are severely affected.

3 The Role of Job-to-Job Transitions for Involuntary Part-Time Employment

Author: Anna Hartmann

3.1 Introduction

Over the last two decades the U.S. labor market experienced a pronounced slowdown in workers' job mobility (cf. Bjelland et al., 2011; Molloy et al., 2016). Especially during the 2001 and 2007-2009 recessions, job-to-job transitions of workers collapsed, which was followed by a slow recovery (cf. Hyatt and Spletzer, 2013; Hyatt, 2015).[1] At the same time, the prevalence of involuntary part-time work strongly increased and, despite the fact that unemployment has declined to its pre-recessional level, many workers were unable to return to full-time employment (cf. Glauber, 2017; Valletta et al., 2020). These developments attract attention among researchers and in the political discussion for two reasons: First, job-to-job transitions contribute significantly to workers' wage growth.[2] Second, involuntary part-time workers are earning less income, are more likely to suffer from poverty, and are working under poorer conditions.[3]

The job ladder, by which workers move from low productivity firms to high productivity firms via direct job-to-job transitions, is important both in steady state and over the cycle. Job-to-job transitions serve as career step, thus allow to realize wage gains and respond strongly to the business cycle, dropping substantially during recessions and increasing during expansions (cf. Haltiwanger et al., 2018b). As reported by Hahn et al. (2020), a large fraction of these job-to-job transitions is associated with changes in hours worked. Even though working part-time involuntarily has sizeable income and work condition consequences, in contrast to wages, the role of hours for workers' job mobility does not receive any attention in the job ladder

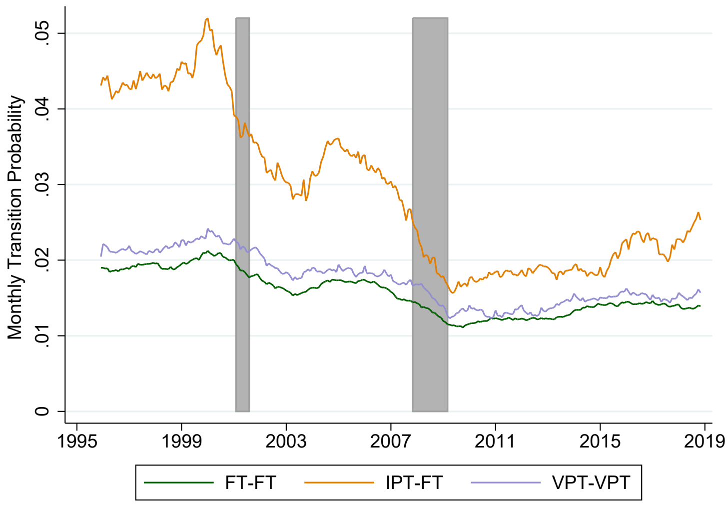
[1] A job-to-job transition appears when an employed worker moves directly to a new employer.

[2] As reported by Hyatt (2015), job-to-job transitions lead on average to wage increases of 3.5-9%. As reported by Haltiwanger et al. (2018b), the slowdown in workers' reallocation during the Great Recession was accompanied by sizeable earning consequences, with a drop in earnings growth by 40%.

[3] Golden (2016) argues that, besides earning less due to hours worked, involuntary part-time workers earn lower wage rates, have a lower degree of benefit coverage, and are affected by work schedules that are more variable and unpredictable. Glauber (2013) shows that involuntary part-time workers, compared to full-time workers, have an over 30.000$ lower median family income and an around five times higher probability of experiencing poverty.

literature. I argue that by focusing on wages an additional important dimension of job-to-job transitions is neglected: Hours worked per worker.

Figure 3.1. Transition Probability by Job Transition Status, 1996 – 2018



Notes: All flows are constructed using monthly CPS data. FT-FT denotes flows from full-time to full-time employment, IPT-FT denotes flows from involuntary part-time to full-time employment, VPT-VPT denotes flows from voluntary part-time to voluntary part-time employment. All flows are defined as direct worker movements between employers. I plot twelve-months moving averages of monthly data. Grey bars denote NBER recession dates.

Motivated by both the changes in the overall job mobility in the U.S. and the severe increase in involuntary part-time employment, this paper provides an empirical and analytical analysis on how working hours affect workers' job mobility. In Figure 3.1, I present two new stylized facts on the job mobility of involuntary part-time workers. First, before the 2001 Recession the average job-to-job transition rate from involuntary part-time to full-time (IPT-FT) employment was more than twice as high as the average job-to-job transition rate from full-time to full-time (FT-FT) and voluntary part-time to voluntary part-time (VPT-VPT) employment. Thus, to find full-time employment, involuntary part-time workers move at a higher pace between jobs than unrestricted workers. Second, a particular strong downward trend can be observed for the job-to-job transition rate from involuntary part-time to full-time employment over the last two decades. Although the job mobility has dropped across all worker types, the decline in the job-to-job transition rate from involuntary part-time to full-time employment was nearly twice as large as for all other employment transitions.

My empirical analysis shows that the strong trend decline of the job-to-job transition rate from involuntary part-time to full-time employment is not connected to simple structural changes or changes in worker demographics and characteristics. Motivated by the literature on the negative scarring effect of unemployment (cf. Arulampalam, 2001; Eriksson and Rooth, 2014) as well as mismatch and nonstandard employment (cf. Fouarge and Muffels, 2009; Pedulla, 2016; Nunley et al., 2017; Biewen et al., 2018), I argue that a plausible research direction is the analysis of a firm-side mechanism. The proposed channel connects changes in firms' hiring behavior to workers' employment opportunities in dependence on their current employment status. The idea behind this mechanism is quite simple: When firms hire workers selectively, they base their hiring decision on informations over workers' employment histories and prefer to hire full-time over involuntary part-time workers. This leads to a scarring effect of involuntary part-time employment, which comprises the negative effect of this employment status on worker's employment opportunities. I present evidence that firms have filled vacancies more selectively over time, in that they have placed a higher weight on workers' employment histories when recruiting, and thus that the scarring effect of involuntary part-time employment has gained importance. This scarring effect displays additional costs of involuntary part-time employment, which are neglected in the literature. Together with the increased prevalence of involuntary part-time employment, I argue that the slowdown of job-to-job transitions hits involuntary part-time workers harder than all other types of worker.

I explain my main empirical findings in an on-the-job search model, in which poaching offers are characterized by wages and working hours. In this novel theoretical framework, involuntary part-time employment generates an hours ladder, which reallocates workers to full-time positions. The model is used to analyze the effect of involuntary part-time employment on workers' job-to-job transition rates and to explore the interplay between recruitment and workers' job mobility. In the model, involuntary part-time workers exhibit a higher job-to-job transition rate than workers not restricted in their amount of hours worked because the former accept a wider range of job offers. When firms fill vacancies selectively, they screen out involuntary part-time workers when recruiting, which makes it harder for workers to move to full-time positions on-the-job and to resolve their work hours mismatch. In the model, involuntary part-time employment entails a scarring effect on workers' job opportunities through selective hiring of firms and therefore also on workers' job-to-job transition rates. The prevalence of this scarring effect depends crucially on the degree of selective hiring in the model. A higher degree of selective hiring deteriorates the employment opportunities of involuntary part-time workers, which makes transitions to full-time employment slow.

The remainder of the paper is organized as follows. An overview of the related literature is presented in Section 3.2. Section 3.3 provides the empirical results on involuntary part-time employment and workers' job mobility. The basic model is described in Section 3.5 and extended to incorporate selective hiring in Section 3.5. Section 3.6 discusses the results with a focus on policy implications. To conclude, the results are summarized in Section 3.7.

3.2 Related Literature

This paper provides a link between two strands of literature: The empirical literature on involuntary part-time work and both the empirical and theoretical literature on workers' job mobility. Despite the fact that the sluggish recovery after the Great Recession has led to a constantly higher level of involuntary part-time employment, the hardships faced by these people have received only little attention in the literature.[4] By analyzing the cyclical properties of involuntary part-time employment, Borowczyk-Martins and Lalé (2020, 2018) highlight that since the Great Recession the risk of being forced into involuntary part-time employment for full-time workers is even greater than the risk of becoming unemployed. Furthermore, Lariau (2018) reports a strong volatility and countercyclicality of involuntary part-time employment. Cajner et al. (2014), Golden (2016), and Valletta et al. (2020) provide evidence for an important structural component, driving involuntary part-time employment since the Great Recession. As reported by Valletta et al. (2020), this component explains about one percentage point of the elevated involuntary part-time employment level. Furthermore, Golden (2016) connects the increased level of involuntary part-time employment to a higher utilization of part-time work in industries which usually exhibit a high part-time share. While all of these papers provide interesting insights on involuntary part-time employment none takes into account the role that job-to-job transitions play for moving to full-time positions, even though Martinez-Granado (2005) and Knaus and Otterbach (2019) show that hours worked are more variable between jobs.[5] I complement these findings by focusing on job-to-job transitions rather than within-firm reallocation of workers between part-time and full-time jobs.

A large empirical and theoretical literature shows that workers move up a job and wage ladder, from low productivity (and low wage) firms to high productivity (and high wage) firms, via job-to-job transitions.[6] By introducing an hours dimension, this paper contributes to the literature on search and matching models with on-the-job search, which was started by Burdett and Mortensen (1998). As shown by Haltiwanger et al. (2018b), on-the-job search enables workers to overcome search frictions, provides matches to better firms and thus significantly contributes to workers career trajectories. Although the theoretical on-the-job search literature focuses exclusively on the job and wage ladder, Hahn et al. (2020) present empirical evidence for an hours ladder, by which workers move via job-to-job transitions to jobs with longer hours. By showing that many job-to-job transitions involve changes from short to long working hours, they conclude that hours worked play a crucial role in determining workers' decisions of moving to a new employer. I build on their empirical evidence on the existence of an hours ladder, and complement this finding by analyzing both empirically and theoretically the connection between workers' job mobility and involuntary part-time employment.

Moscarini and Postel-Vinay (2016) and Haltiwanger et al. (2018b) analyze the behavior of job-to-job transitions during the Great Recession, neglecting the important role played by working hours. As shown by Moscarini and Postel-Vinay (2016), the job ladder collapsed during the

[4]Valletta (2018) shows that this amounted to 1.4 million additional involuntary part-time workers in 2018.

[5]Martinez-Granado (2005) shows that the changes in working hours for job movers, in comparison to stayers, exhibit a six times higher variance. Knaus and Otterbach (2019) find that job moves of mismatched workers result in an hours adjustment which is twice as large as the adjustment of mismatched job stayers.

[6]For a theoretical framework see Burdett and Mortensen (1998) and Moscarini and Postel-Vinay (2013). For an empirical anlysis see Kahn and McEntarfer (2014), Moscarini and Postel-Vinay (2016), and Haltiwanger et al. (2018a,b).

Great Recession and struggled to recover to its pre-recessional level. Haltiwanger et al. (2018b) present evidence for an equally dramatic slowdown in the wage ladder, characterized by a strong drop in job-to-job transitions to high wage firms. In addition, as reported by Bjelland et al. (2011), Hyatt and Spletzer (2013), and Molloy et al. (2016), there has been a strong trend decline in overall job mobility since the early 2000's. Molloy et al. (2016) evaluate several possible causes for this development. The key results from their analysis is that demographic changes can only explain little of the overall decline and that the pattern is not driven by shifts in the industry composition, improvements in worker-firm matching or by regulations in the labor markets. Furthermore, Hyatt and Spletzer (2013) provide empirical evidence that the slowdown in overall job-to-job flows, by around 50% between 1998 and 2010, was concentrated during recessions, i.e. followed a "stair-step" pattern. I contribute to these findings by emphasizing that the drop in overall job mobility is likely to be especially harmful for involuntary part-time workers. Therefore, I focus on analyzing the relative development in workers' job-to-job transitions over time and providing a mechanism explaining the relative strong decline for involuntary part-time employment.

3.3 Empirical Evidence: Job Mobility and Involuntary Part-Time Employment

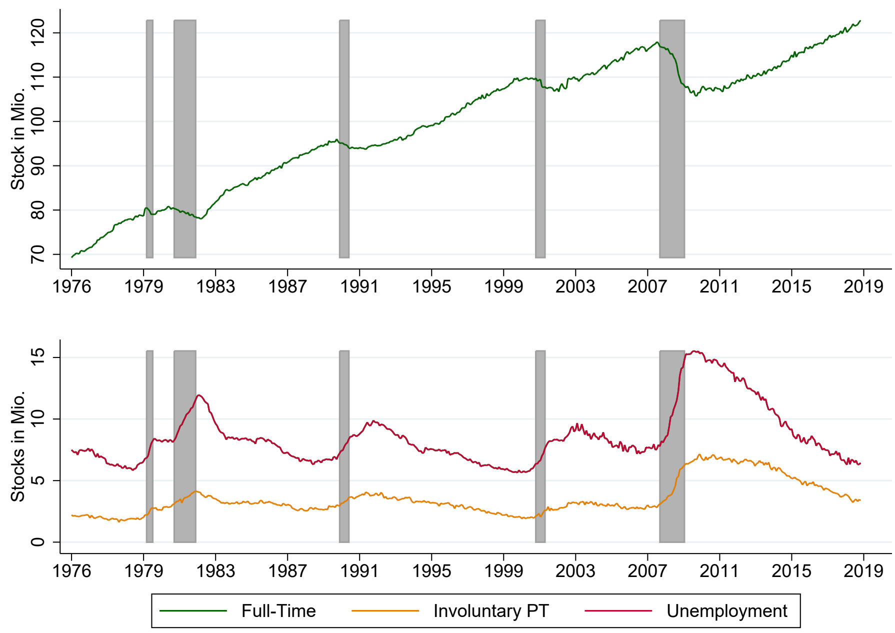
In this section, I provide empirical evidence for the development in workers' job mobility across employment types, highlighting several characteristics of the behavior of involuntary part-time workers. I show that the strong trend decline in the job-to-job transition rate from involuntary part-time to full-time employment can be connected to a scarring effect of involuntary part-time employment on workers' employment opportunities. Additionally, several plausible explanations that are connected to changes in the industry composition, worker demographics and characteristics are ruled out. The relevance of each channel is evaluated by considering the within category job mobility of workers. To this end, I perform a decomposition analysis, which shows that none of these industry and worker components act as a main trigger for the reported pattern.

3.3.1 Data Sources and Construction

I use data on full-time and part-time employment from the Current Population Survey (CPS). Full-time work is defined as working 35 hours or more per week. Households in the CPS are included for eight months in total and for four consecutive months: Before they are again included for four months, they are not interviewed for eight months. Only since the CPS redesign in 1994 part-time workers are asked whether they are willing or able to work in full-time employment and if they are still working for the same employer (cf. Polivka and Miller, 1998). Furthermore, samples before and after May 1995 cannot be linked using household identifiers since the CPS changed household numbering. Due to this issues, the sample is selected to run from 1996 to 2018.

I link consecutive months in the CPS using the unique individual identifier (CPSIDP) provided by the Integrated Public Use Microdata Series (IPUMS).[7] Implausible matches are excluded from the merged dataset, checking for gender, race and age differences. In the CPS part-time employment is categorized into two types: workers who are part-time employed voluntarily ("non-economic reasons") and involuntarily ("economic reasons"). I am mainly interested in job-to-job transition rates. Thus, flows between three different employment types are considered: full-time, involuntary part-time and voluntary part-time. To obtain monthly transition rates for each employment type, IPUMS longitudinal weights for linking adjacent months (PANLWT) are applied.

Figure 3.2. Employment Stocks, 1976 – 2018



Notes: Data is taken from Borowczyk-Martins and Lalé (2019). They provide adjusted monthly IPT employment stocks and flows from 1976 to 2018 using CPS data. Grey bars denote NBER recession dates.

3.3.2 Employment Changes

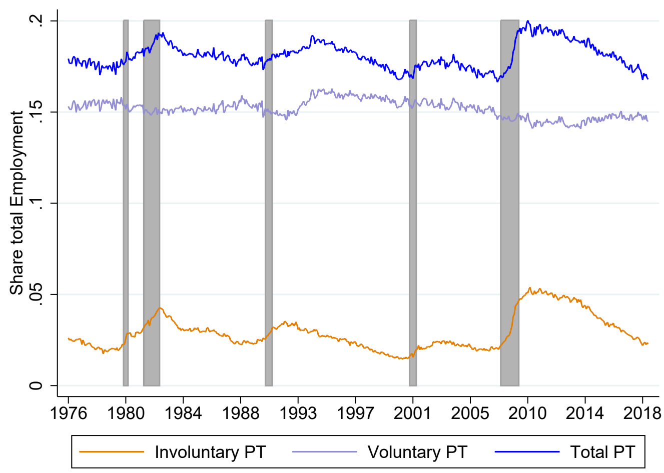
In this section, I give an overview of the development in employment stocks across worker types. Figure 3.2 illustrates an increase in the stock of full-time (FT) employment from 1979 onwards, which was interrupted during recessions and especially during the Great Recession. Involuntary part-time (IPT) work and unemployment shows a strong co-movement, implying that IPT employment exhibits a high volatility and countercyclicality. Both series increased

[7] I use IPUMS data from Flood et al. (2020).

strongly during recessions, but IPT employment declines even more slowly than unemployment. As a result, the two series have stayed close and the share of IPT employment to unemployment stayed quite high since the Great Recession. This is in line with Cajner et al. (2014), Golden (2016), and Valletta et al. (2020), who show that a structural component is driving the level of IPT employment since the Great Recession, which can mainly be explained by changing industry employment composition. Furthermore, Farber (2017) reports that the high probability of losing a job during the Great Recession has been accompanied by low re-employment rates and a strong negative effect on workers' probability to move into FT employment.[8]

Figure 3.3 displays the behavior of the two different types of part-time (PT) employment. The IPT and voluntary part-time (VPT) employment shares exhibit very different patterns since 1976. Even though VPT employment comprises most of the share of PT work, overall PT employment is mainly driven by the cyclicality of IPT work, experiencing a pronounced increase during the Great Recession.

Figure 3.3. Part-Time Employment Shares, 1976 – 2018



Notes: Data is taken from Borowczyk-Martins and Lalé (2019). Grey bars denote NBER recession dates.

3.3.3 Job-to-Job Transitions

Particularly in the light of the elevated level of IPT employment, workers' employment opportunities have become even more important. Besides the level of IPT employment also the slowdown in workers' overall job mobility raises concerns that workers stuck in IPT jobs. To asses the degree by which IPT workers are affected by decreasing job mobility, I consider the job-to-job transition rate of workers by employment status.[9]

[8]Farber (2017) finds that the problem of finding FT employment from unemployment is the main source for costs arising from workers' job loss since the Great Recession.

[9]The job-to-job transition rates are calculated considering all direct worker movements between employers for each transition category relative to all employed workers in the initial category.

Table 3.1. Changes in Transition Probabilities by Transition Status

	Long Term	2001 Recession	Great Recession
FT-FT	-33.2%	-16.0%	-20.5%
IPT-FT	-55.8%	-28.4%	-38.2%
VPT-VPT	-34.7%	-16.1%	-22.7%

Notes: Monthly CPS data. Changes are reported between 3 different time periods: before the 2001 Recession from 1996m01-2001m02, between the two Recessions from 2001m12-2007m11 and after the Great Recession from 2009m7-2018m12. Column 1 shows long term changes from before the 2001 Recession to after the Great Recession. Column 2 shows changes for the 2001 Recession. Column 3 shows changes for the Great Recession.

As shown in Figure 3.1, both the level and development in workers' job mobility vary widely between IPT and FT or VPT work. The job-to-job transition rate from IPT to FT (IPT-FT) employment before the Great Recession was more than twice as high than the job-to-job transition rate from FT to FT (FT-FT) employment and VPT to VPT (VPT-VPT) employment.[10] When considering the development of the job-to-job transition rates by worker type, strikingly, the trend decline seems to be particular strong for IPT workers. As reported in Column 1 of Table 3.1, despite the fact that the job mobility has slowed across all worker types, the IPT-FT job-to-job transition rate dropped on average by 55.8% between 1996 and 2018 in comparison to 33.2% and 34.7% for FT and VPT workers, respectively.[11] By comparing Column 2 and 3 of Table 3.1, it can be seen that the drop of the job-to-job transition rates for every job transition status is more pronounced during the Great Recession than for the 2001 recession. Thus, besides the job and wage ladder, also the hours ladder slowed substantially during the Great Recession.

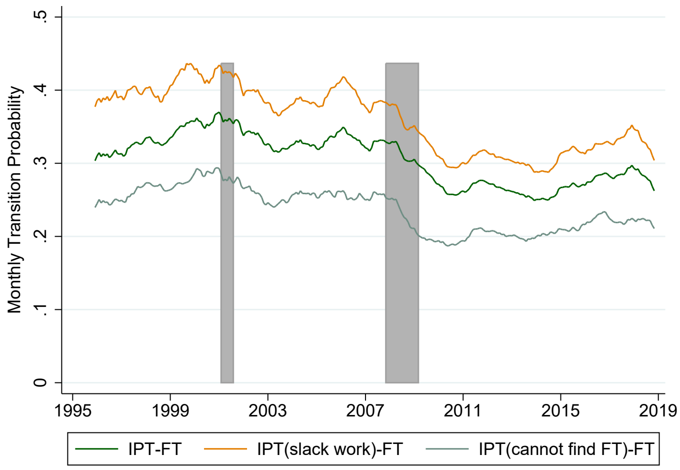
When considering the reported pattern of IPT-FT job-to-job transitions, the question arises whether it can be explained by IPT workers waiting on-the-job to switch to FT positions rather than moving between employers. Figure 3.4 reports the overall IPT-FT transition rates (job-to-job and within a firm) by IPT type, for workers that are IPT employed due to slack work or because they cannot find FT employment. The overall as well as the transition rates by IPT type have been decreasing since 1996. Furthermore, the within-firm IPT-FT transition rate decreased by around 20% between 1996 and 2018.[12] Therefore, the pronounced drop in the IPT-FT job-to-job transition rate is not caused by workers waiting within a firm to move to FT positions.

[10] As reported by Meisenheimer and Ilg (2000), in the late 1990's IPT workers exhibit a much higher job search probability in comparison to FT or VPT workers. They find that, in 1999, 11.9% of IPT workers searched for a new job compared to 4.0 percent for FT and VPT workers.

[11] The IPT-FT job-to-job transition rate is slightly more cyclical than the job-to-job transition rates of all other worker types, see Figure B.1. When comparing the cyclicality of the FT, IPT, and VPT employment shares the same pattern arise, with IPT employment shares being more cyclical than all other employment types, see Figure B.2.

[12] See Figure B.3.

Figure 3.4. Overall IPT-FT Transitions Rates, 1996 – 2018



Notes: All flows are constructed using monthly CPS data. I plot twelve-months moving averages of monthly data. Grey bars denote NBER recession dates.

Job-to-Job Transitions: Industries

There is evidence that the persistent rise in the stock of IPT work since the Great Recession can be connected to a higher utilization of PT employment (cf. Valletta and van der List, 2015; Golden, 2016; Glauber, 2017). By considering job-to-job transitions within and between different industries, I analyze if the changes in the demand for PT employment and in the relative job mobility of workers are linked. Since the share of PT employment is mostly increasing in industries which usually rely more strongly on PT work, I compare workers' job mobility in industries most affected by the structural shift to less affected industries.[13]

Table 3.2. Within Industry Changes in Involuntary Part-Time Transition Probabilities

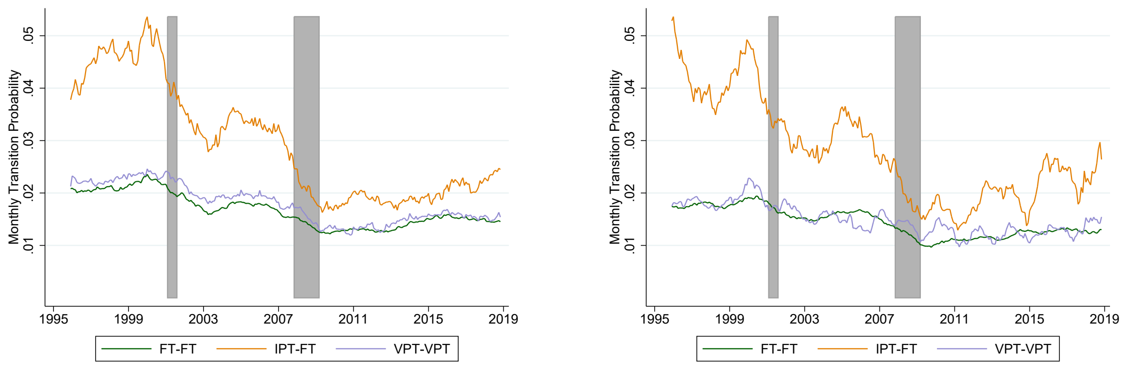
	Long Term	2001 Recession	Great Recession
Retail, Leisure, Hospitality	-60.6%	-34.5%	-39.8%
Other Services	-56.0%	-24.5%	-41.6%
Non Services	-54.0%	-29.7%	-34.6%

Notes: Monthly CPS data. Transition probabilities are calculated considering only switches within industries for each category. Changes are reported for 3 different time periods: before the 2001 Recession from 1996m01-2001m02, between the two Recessions from 2001m12-2007m11 and after the Great Recession from 2009m7-2018m12. Column 1 shows long term changes from before the 2001 Recession to after the Great Recession. Column 2 shows changes for the 2001 Recession. Column 3 shows changes for the Great Recession.

[13]As reported by Golden (2016), 54.3 % of the IPT employment growth from 2007 to 2015 can be explained by changes in the retail trade, and leisure and hospitality industry. Taken together with educational and health services, and professional and business services, these industries are accountable for 85.0 % of the IPT employment growth.

Table 3.2 reports changes in the within-industry transition rate of IPT workers for three different time periods and industries. The first and second category comprise industries most affected by the structural shift in PT employment and the third category comprises less affected industries. The drop in job-to-job transition rates is present within all three categories but slightly more pronounced in industries most affected by the structural shift. The within-industry job-to-job transition rates have been slowing for all worker types, with the trends across employment types in the retail, trade, and hospitality sector exhibiting the most similar pattern.[14]

Figure 3.5. Transition Probability by Job Transition Status and Industry of Origin, 1996 – 2018



(a) Retail Trade and Services

(b) Non Services

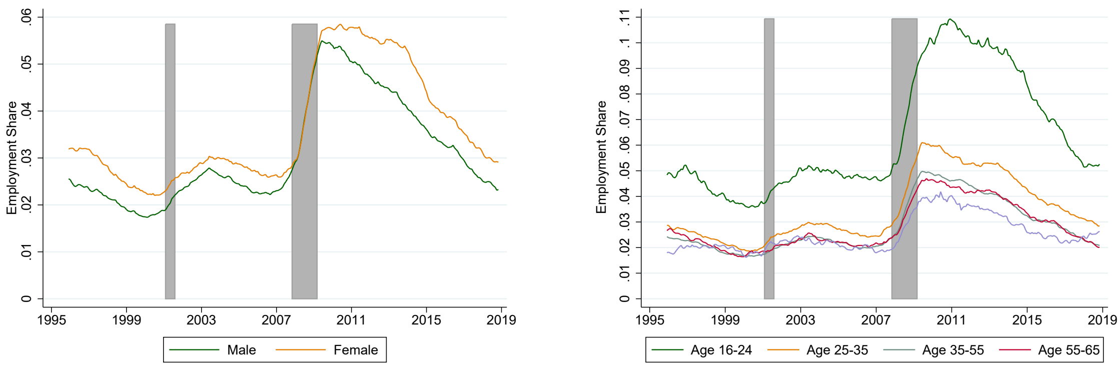
Notes: All flows are constructed using monthly CPS data. I plot twelve-month moving averages of monthly data. Panel (a) shows the job mobility for workers switching from the retail trade, leisure and hospitality, educational and health services, and professional and business services industry. Panel (b) shows the job mobility for workers switching from all other industries. Grey bars denote NBER recession dates.

Additionally, I construct workers' job mobility between different industry categories. Figure 3.5 depicts monthly job-to-job transition rates from industries contributing mainly to increasing PT employment shares, Panel 3.5a, and from all other industries, Panel 3.5b. When looking at different industries of origin, job-to-job transitions show the same development as documented in Figure 3.1. The pronounced drop in job-to-job transition rate for IPT workers is present within both industry categories but is slightly more pronounced in industries with a strong increase in PT employment.[15]

Taken together, I find that the reported pattern persists when considering transitions within and between different industries, i.e. the pronounced drop in job-to-job transition rate for IPT employment is not driven by structural changes in a specific industry.[16] This is in line with evidence presented by Molloy et al. (2016), who find that industry shifts cannot explain the trend decline in workers' overall job mobility. Unsurprisingly, the within industry job-to-job

[14]See Figure B.4.
[15]See Table B.1.
[16]For a formal decomposition analysis see Section 3.3.4.

Figure 3.6. Involuntary Part-Time Employment Shares of the total within Group Employment, 1996 – 2018

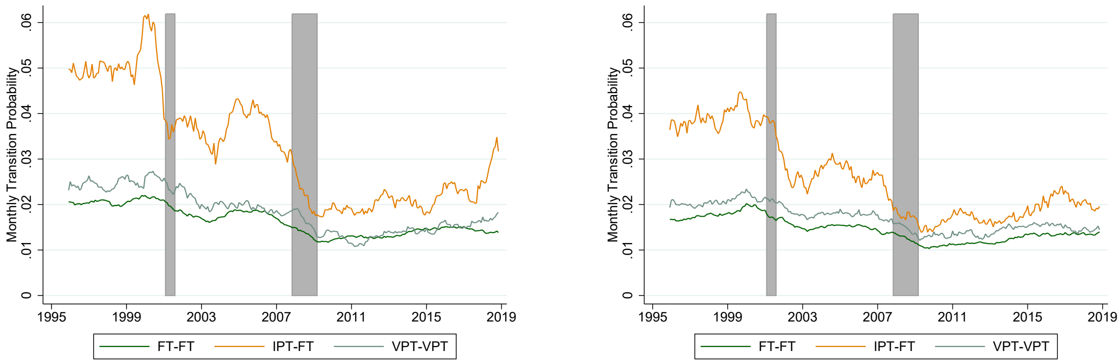


(a) Males and Females

(b) Age Groups

Notes: Shares are constructed using monthly CPS data. I plot twelve-month moving averages of monthly data. Grey bars denote NBER recession dates.

Figure 3.7. Transition Probability by Jobs Transition Status and Gender, 1996 – 2018



(a) Males

(b) Females

Notes: All flows are constructed using monthly CPS data. I plot twelve-months moving averages of monthly data. Grey bars denote NBER recession dates.

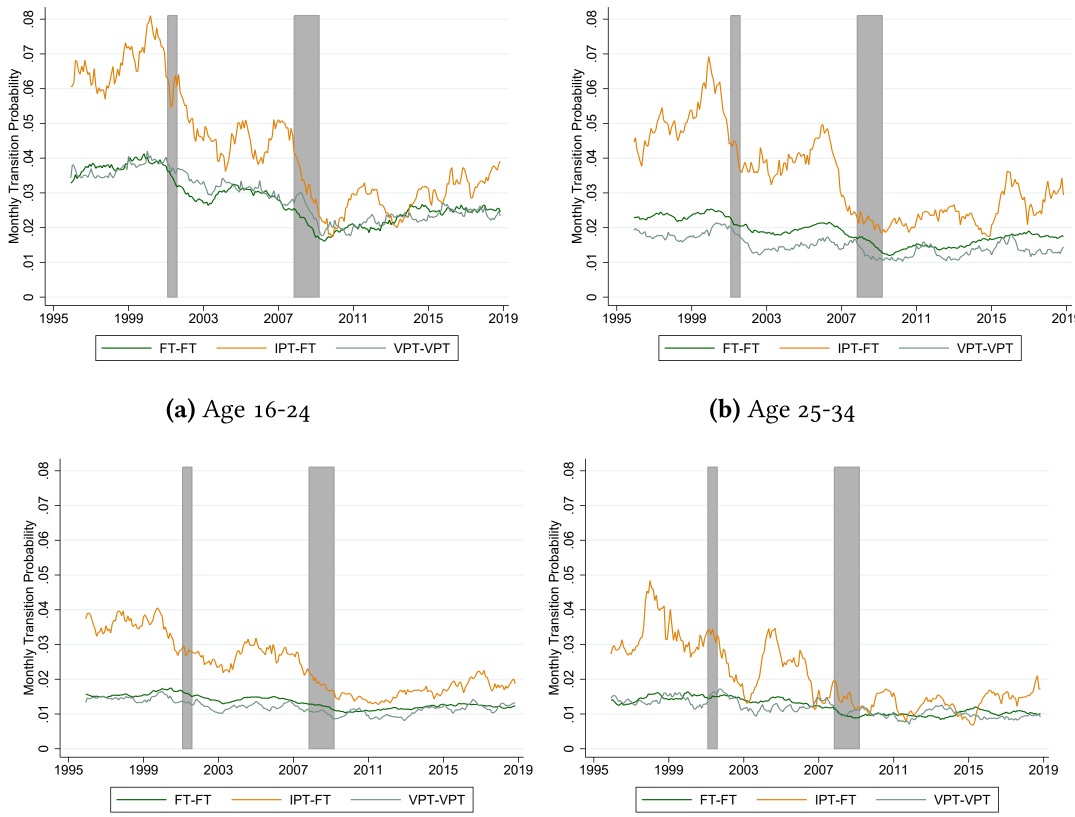
transition rate for IPT workers is on average smaller in industries in which PT employment is more prevalent than in industries with a higher share of FT jobs.[17]

Job-to-Job Transitions: Worker Demographics

Conditional on workers' demographics the share of IPT employment differs considerably. Figure 3.6 plots the IPT employment shares by gender and for different age groups. Females are more likely to be IPT employed than males. Young workers are much more likely to be IPT employed than seniors. The average age exhibits an upward trend for FT, IPT and VPT workers since 1996, with IPT workers being on average the youngest among all worker types.[18] As can

[17] See Table B.2.
[18] See Figure B.5.

Figure 3.8. Transition Probability by Job Transition Status and Age, 1996 – 2018



(a) Age 16-24

(b) Age 25-34

(c) Age 35-54

(d) Age 55-65

Notes: All flows are constructed using monthly CPS data. I plot twelve-months moving averages of monthly data. Grey bars denote NBER recession dates.

be seen in Figure 3.6, there is also a strong cyclical component influencing IPT employment shares. While there are differences in IPT employment shares among workers conditional on their demographics, they exhibit the same development over time.

I find a similar link between workers' demographics and job mobility. The results are depicted in Figures 3.7 and 3.8. Males exhibit higher job-to-job transition rates for both IPT and FT workers in comparison to females. Despite these differences, the overall pattern emerges for both groups, showing the strongest trend decline for IPT work. As can be seen in Figure 3.8 the youngest workers exhibit the highest job-to-job transition rate for both, IPT and FT workers. Which is not surprising, since these workers are on average more mobile than older workers (cf. Bjelland et al., 2011; Ouimet and Zarutskie, 2014; Molloy et al., 2016). What is striking is that the gap between the IPT-FT and FT-FT transition rate is quite small for the youngest worker group.[19] Nevertheless, the trend decline is persistent across all four age groups. It follows that changes in worker demographics are not driving the strong downward trend in the IPT-FT job-to-job transition rate.[20]

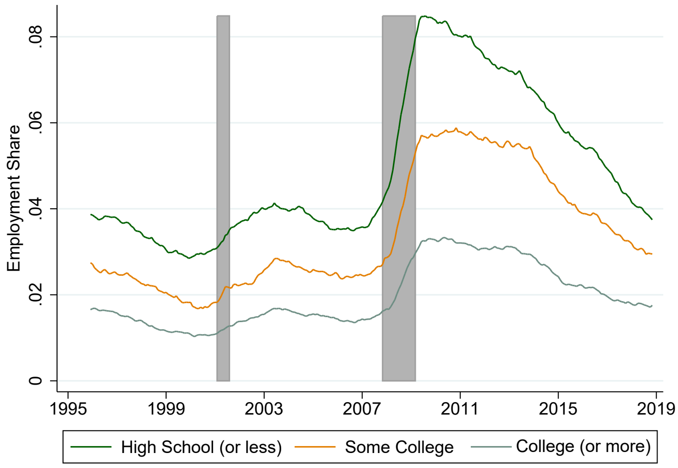
[19]See Figure B.6.

[20]This is in line with Molloy et al. (2016), who find that demographics explain only a small fraction of changing

Job-to-Job Transitions: Education

It is well known that the labor demand has shifted across skills and education over the past decades (cf. Autor and Dorn, 2013). I start by analyzing the development in IPT employment shares by different educational groups. As can be seen in Figure 3.9, the IPT employment share for each educational group is strongly countercyclical. Less educated workers are more likely to be IPT employed than skilled workers. Similar to the results for worker demographics, while employment shares differ in level between educational groups, they show the same development.

Figure 3.9. Involuntary Part-Time Employment Shares of the total within Group Employment, 1996 – 2018



Notes: Shares are constructed using monthly CPS data. I plot twelve-month moving averages of monthly data. Grey bars denote NBER recession dates.

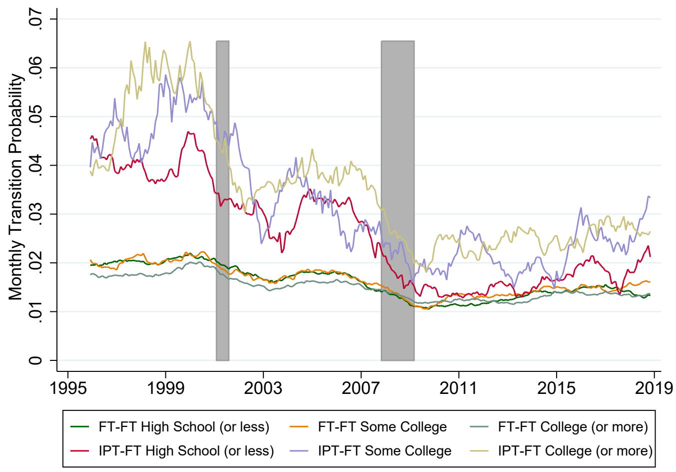
With respect to workers' job mobility, I consider a possible link between workers' education and a shift in the demand for skills. Related to this, Hedtrich (2019) shows that the declining overall job mobility can be connected to the polarizing labor demand structure away from routine occupations.[21] Following Hedtrich (2019), I employ the educational level as a proxy for workers' skill. As can be seen in Figure 3.10, I find that the IPT-FT and FT-FT job-to-job transition rates have been declining for all three educational groups. While the overall pattern in job-to-job transition rates can be found when considering different educational groups, the decline in the IPT-FT transition rate in comparison to the FT-FT transition rate is steepest among middle skilled workers who are affected the most by the changing demand structure and polarization.[22]

overall workers' job mobility.

[21] The main argument of his paper is that, by displacing middle skilled workers, routine-biased technological change makes it harder for low-skilled workers to find better jobs. Whereas, high-skilled workers start their careers further up the job ladder because stepping-stone jobs are harder to find. Additionally, rising educational attainment strengthen the competition for better jobs.

[22] See Figures B.7 and B.8.

Figure 3.10. Transition Probability by Job Transition Status and Education, 1996 – 2018



Notes: All flows are constructed using CPS data. I plot twelve-month moving averages of monthly data.

3.3.4 Decomposition Analysis

While there are differences in the development of the job-to job-transition rates among different industries and workers with different demographics and characteristics, the overall pattern remains quite robust. In this section, I decompose changes in job-to-job transition rates into industry, gender, age and educational effects by applying the methodology introduced in Autor et al. (2003). I use this decomposition exercise to evaluate the relative importance of each of those components for the change in job-to-job transition rates for IPT versus FT workers over the last decades. The implied change, reported in Column 3 of Table 3.3, measures the effect of a change in the job-to-job transition rate for a specific industry, gender, age and education group, keeping the employment share of that group constant on the 1996 level. Column 4 of Table 3.3 reports the percentage difference between the implied changes for each category and the drop in the overall transition rate, i.e. the real change.[23]

In line with the reported results across industries, demographics and worker characteristics, I find that only a small part of the drop in workers' job mobility can be explained by simple structural changes. As can be seen in Column 4 of Table 3.3, a changing gender and age structure has a negative impact on the job-to-job transition rates of workers. With regard to the gender category, the drop in the job-to-job transition rate for FT and IPT workers would have been 0.18% and 0.40% smaller if the employment shares had remained constant since 1996. The age category shows the strongest negative change, where 12.56% and 7.95% of the drop in the overall FT-FT and IPT-FT transition rate can be explained by shifts in the age structure of workers over time. In contrast, changing employment shares among different industries and educational groups even lead to a positive effect on the job-to-job transition rates for

[23]The drop in the overall transition rate between 1996 and 2018 amounts to around 42% from IPT-FT and around 26% from FT-FT employment.

Table 3.3. Decomposition of Changes in Transition Rates, 1996 – 2018

Category	Transition	Implied Changes	% Changes
Industry	FT-FT	-27.11	1.85
	IPT-FT	-43.21	1.94
Gender	FT-FT	-26.25	-0.18
	IPT-FT	-42.39	-0.40
Age	FT-FT	-22.95	-12.56
	IPT-FT	-39.17	-7.95
Education	FT-FT	-25.77	-1.74
	IPT-FT	-44.38	4.53

Notes: Monthly CPS data. Column 3 reports implied changes in the transition probabilities, which are calculated considering the 1996 employment shares in the category. Column 4 reports the % changes between the drop in the implied transition rates with constant employment shares and the drop in the real transition rates.

IPT workers. The drop in the FT-FT and IPT-FT transition rate would have been 1.85% and 1.94% stronger if the industry employment composition stayed constant between 1996 and 2018.[24] Taken together, changes in the industry composition or worker demographics and characteristics are unlikely to be the main driving force behind the development in workers' job mobility.

3.3.5 Scarring Effect and Selective Hiring

It is well-established that histories of unemployment are likely to entail a scarring effect, influencing workers' employment opportunities. When firms assume that spells of unemployment provide informations over workers' quality, firms include this information in their hiring decision and workers are affected by an unemployment penalty.[25] Even though there is substantial evidence for a negative effect of unemployment on workers' employment opportunities and wages (cf. Arulampalam, 2001; Eriksson and Rooth, 2014; Nilsen and Reiso, 2011; Birkelund et al., 2017; Guvenen et al., 2017; Shi et al., 2018), there is little evidence on how firms use informations over IPT employment when recruiting.

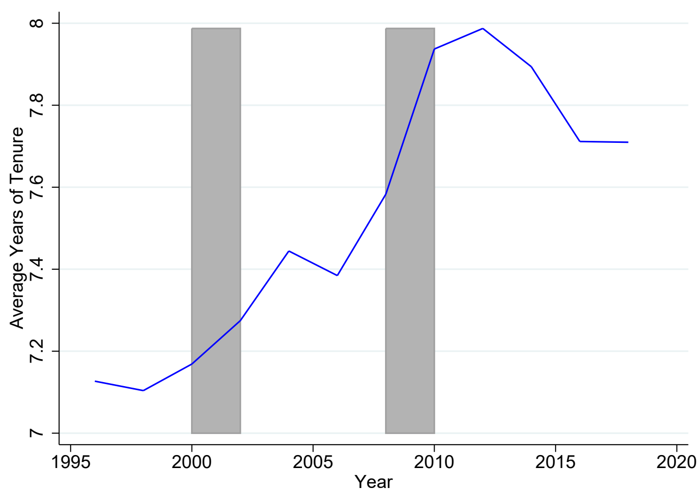
When employment histories are taken into account when recruiting, as indicated by the scarring effect of unemployment, firms may also prefer FT over IPT workers. In this context, Pedulla (2016) shows that firms use information on nonstandard and mismatch employment as

[24] I find a positive influence of industries, even though the drop in worker's job mobility is on average stronger for the retail trade and service industries, since I compare 1996 to 2018.

[25] For evidence on a signalling effect of unemployment see Eriksson and Rooth (2014) and Pedulla (2016).

signals over workers' competence levels and thereby affecting workers' employment opportunities. For instance, Pedulla (2016) argues that these competence signals are most negative if workers' employment histories include a recent involuntary job loss or the inability to find FT and standard employment. With respect to workers' interview likelihood, Pedulla (2016) shows that firms strongly penalize men for histories of PT employment, underemployment, and unemployment. Furthermore, he argues that firms use IPT employment as an indicator that workers' competence or productivity levels are not sufficient to work in FT positions. Regarding mismatch employment, Nunley et al. (2017) show that firms read histories of underemployment as signals, resulting in a thirty percent lower callback rate for these workers. Since workers' preferences are not matching with their current employment status, Pedulla (2016) also interprets IPT work as mismatch employment in the same way as underemployment. He shows that underemployment leads to a strong scarring effect for workers. With regard to wages, Biewen et al. (2018) shows that histories of employment interruptions and temporary PT employment are important for explaining the higher wage inequality for FT workers, considering German data. Using British, German, and Dutch data, Fouarge and Muffels (2009) find that PT employment leads to a scarring effect on workers' wages, which size depends on the length of the PT episode. Taken together, IPT workers are likely to be screened out by firms, leading to a scarring effect on their employment opportunities and thus on their job-to-job transition rate.

Figure 3.11. Average Years of Job Tenure, 1996 – 2018



Notes: CPS data. The sample is restricted to individuals of age 25-65. Grey bars denote NBER recession dates.

Motivated by the evidence on a scarring effect of IPT employment, I propose a firm-side mechanism driving the reported pattern. The essence of this mechanism is the interaction between firms' perceptions over workers, depending on their current employment status, and how these perceptions shape firms' recruitment decisions. I connect the strong trend decline in the IPT-FT job-to-job transition rate to a higher degree of selectivity of firms when recruiting.[26] An observation supporting this firm-side mechanism is the development of workers' within firm job tenure. Figure 3.11 shows that workers' job tenure increased from 1996 onwards for workers aged 25-65.[27] The increasing job tenure can be seen as an indicator that firms rely less on the possibility of screening workers on the job rather than in advance. Compared to workers' job-to-job transitions, the development in workers' tenure mirrors the transition pattern over time. Furthermore Pedulla (2016) argues that the share of non-standard and mismatch employment increased simultaneously with firms' utilization of the external labor market, resulting in less direct information about applicants for firms.[28] He concludes that these changes in firms' hiring behavior have made employment histories of workers more relevant when recruiting. An additional indicator for a more selective hiring of firms is the development of the job-to-job transition rates by age. As reported in Table 3.4 and Figure 3.8, the transition rates for both FT and IPT workers exhibit a stronger drop for younger workers. This is in line with a more selective hiring, since young FT workers exhibit the lowest level of work experience, providing less information about their level of competence and thus are more likely to be screened out by firms. In this context, Eriksson and Rooth (2014) show that firms read workers' experience as signals over their productivity. Together with the pronounced drop in the job mobility of IPT workers, it seems to be the fact that workers who provide less information over their quality are affected more by the drop in job-to-job transitions and thus that hiring has become more selective and employment histories have become more relevant.

Table 3.4. Changes in Transition Probabilities by Age Group

Group	FT-FT Change	IPT-FT Change
Age 16-24	-39.5%	-57.3%
Age 25-34	-32.9%	52.4%
Age 35-54	-25.4%	-52.9%
Age 55-65	-30.7%	-52.3%

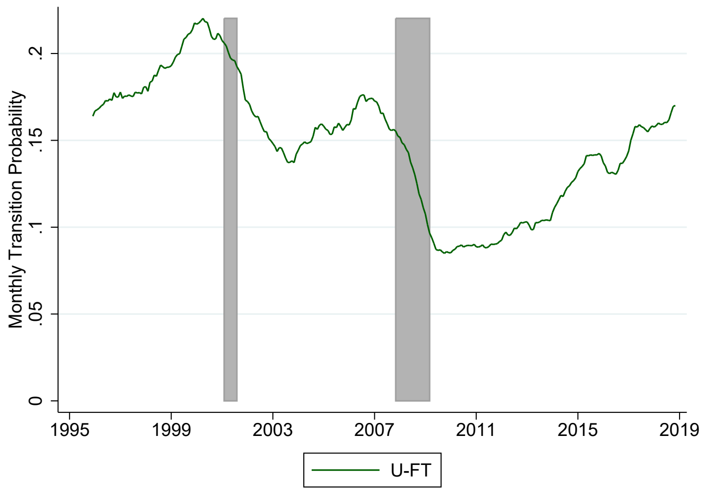
Notes: Monthly CPS data. Transition probabilities are calculated considering switches for each age group. Changes are reported for long term changes from before the 2001 Recession to after the Great Recession for FT-FT and IPT-FT transitions.

[26] This is in line with the literature on the overall drop in workers' job mobility. Molloy et al. (2016) suggest to analyze changes in firms' employment behavior, which could be screening informations, hiring practices or that both workers and firms have become more risk averse.

[27] In the same way, Copeland (2019) reports a shift in workers' tenure distribution towards longer tenure levels until the 2010's. From 2010 onwards, he finds an increase in the share of shorter tenure levels.

[28] Pedulla (2016) argues that this development is a major factor of the "New Economy". Hollister (2011) shows that changes in employment practices are driven by a higher flexibility and focus on short-term outcomes of firms, which may stems from an increase in foreign competition, in specialized away from mass production, or in the pace of technological change. Cappelli (2001) argues that increased competition and the pace of changes on the product market requires a higher flexibility of firms, which makes long-term employment relationships and internal labor markets unprofitable.

Figure 3.12. Overall Unemployment Transitions Rates, 1996 – 2018



Notes: All flows are constructed using monthly CPS data. I plot twelve-month moving averages of monthly data.Grey bars denote NBER recession dates.

To analyze if the relative strong decline in the job-to-job transition rate from IPT-FT employment is driven by firms' hiring behavior, I employ the overall transition rate from unemployment to FT positions as an inverse proxy for the degree of selective hiring in the economy.[29] As reported in Figure 3.12, the transition rate from unemployment to FT employment has been decreasing over the last three decades. In line with this observation, Farber (2017) finds that especially since the Great Recession it has become much harder for workers to find a FT position after a job loss. I am interested in a possible connection between the relative development of the job-to-job transition rate of IPT-FT to FT-FT employment and the employment opportunities of unemployed workers, i.e. the degree of selective hiring. Therefore, I estimate

$$s_{IPT-FT,t} = \alpha + \beta p_{U-FT,t} + \gamma X_t + \eta R_t + \delta_t + \epsilon_t \tag{3.1}$$

where $s_{IPT-FT} = p_{IPT-FT,t}/p_{FT-FT,t}$ is the ratio of the IPT-FT to the FT-FT job-to-job transition rate and $p_{U,FT}$ the transition rate from unemployment to FT positions of workers. X_t is a vector of control variables, including controls for workers characteristics, and industry and occupation composition. The complete list of control variables is provided in B.2. R_t are recession dummy variables, δ_t are month fixed effects and ϵ is the residual.

If IPT employment leads to a scarring effect, I expect to find a negative relationship between the degree of selective hiring by firms and the relative job-to-job transition rate of IPT workers. The results can be seen in Table 3.5. Column (1) reports the regression results, including controls for worker characteristics. The other two columns show that the results do not depend on the selection of control variables. All three columns provide evidence for a positive correlation between the ratio of the job-to-job transition rate of IPT-FT to FT-FT employment and the FT

[29]This is motivated by the literature on the scarring effect of unemployment.

Table 3.5. Regression Results for the IPT-FT Transition Rate

	(1)	(2)	(3)
Transition Rate	3.0333	2.8328	2.9582
From U to FT	(1.0975)	(1.2722)	(1.4735)
	p=0.0061	*p=0.0268*	*p=0.0458*
Observations	276	276	276
R^2	0.3881	0.3997	0.4021
Industry controls	no	yes	yes
Occupation controls	no	yes	yes
Worker controls	yes	no	yes
Import penetration	no	no	yes
Recession fixed effects	yes	yes	yes
Monthly fixed effects	yes	yes	yes

Note: The standard errors are reported in parantheses. The p-values are reported below the standard errors.

job-finding rate of unemployed workers. When unemployed workers become less likely to find a FT position, it becomes harder for IPT workers in comparison to FT workers to find FT positions.

To assess why s_{IPT-FT} is decreasing with the degree of selective hiring, I estimate the effect separately for IPT and FT workers.[30] In the following, I replace s_{IPT-FT} when estimating (3.1) by both the IPT-FT and FT-FT transition rate. As can be seen in Table 3.6, a decreasing FT job-finding rate for unemployed workers is accompanied by both decreasing IPT-FT and FT-FT job-to-job transition rates but with a stronger effect for IPT workers. Both regression results point in the same direction of a scarring effect of IPT employment on workers' chances to find FT positions and that the strength of this effect is connected to the degree with which firms hire selectively.

[30]The negative effect from selective hiring can be triggered by an increase in the FT-FT transition rate or a stronger drop in the IPT-FT than in the FT-FT transition rate.

Table 3.6. Regression Results for the IPT-FT and FT-FT Transition Rate

	(1)	(2)
Dependent variable	IPT-FT transition rate	FT-FT transition rate
Transition Rate	0.0649	0.0091
From U to FT	(0.0247)	(0.0049)
	p=0.0093	*p=0.0662*
Observations	267	267
R^2	0.6761	0.8014
Industry controls	yes	yes
Occupation controls	yes	yes
Worker controls	yes	yes
Import penetration	yes	yes
Recession fixed effects	yes	yes
Monthly fixed effects	yes	yes

Note: The standard errors are reported in parantheses. The p-values are reported below the standard errors.

3.4 A Model with Involuntary Part-Time Employment

To examine the effect of involuntary part-time employment on workers' job mobility, I consider a search and matching model with on-the-job search and wage posting, in which poaching offers are characterized by both wages and working hours. To this end, I extend the discrete time job ladder model presented in Cairó et al. (2016) by incorporating involuntary part-time work and an hours ladder, which reallocates workers to full-time jobs. The model features both full-time and part-time jobs, and workers. Due to these two types of heterogeneity, there are some workers working involuntarily part-time. Workers can search on-the-job and firms can poach workers via higher wages, or in the case of involuntary part-time employment via longer hours. The model is than used in Section 3.5 to analyze the impact of selective hiring of firms on the job-to-job transition rate of involuntary part-time workers.

Workers and Firms

There are two types of firms, $j = FT, PT$, that differ in their amount of working hours offered, either full-time (denoted as FT) or part-time (denoted as PT). The model features a continuum of otherwise homogenous workers with a preference for jobs in firms offering either FT or PT positions. Firms post vacancies $v_j(y_i)$ to hire workers. Due to on-the-job search both unemployed and employed workers search for a new job and firms can, in addition to hire unemployed workers, poach workers from other firms. I follow Cairó et al. (2016) and Lise and Robin (2017) by assuming random search. Firms and workers learn about each others' type during the job interview. Workers with a preference for full-time positions can work in a firm offering either full-time (denoted as FT) or part-time jobs (denoted as IPT). When a worker with a preference for FT positions accepts a job offer from a PT firm, the worker becomes involuntarily PT employed. When employed in a FT firm, workers with a preference for FT positions are not willing to switch to a firm offering a PT position. Workers with a preference for a part-time position (denoted as VPT) can only work in firms offering PT jobs.[31] Thus, when a worker is matched to a vacancy, the worker decides whether or not to accept the poaching offer in dependence on the firm's type. Firms of each type differ with respect to their labor productivity y_i, with $i \in 1, 2$ and $y_1 < y_2$.[32] They produce with technology $f_j(y_i) = A_j y_i$, where $A_{FT} > A_{PT} > 0$, which means that a higher amount of hours worked results in a higher output.

3.4.1 Labor Market Frictions

Matching between workers and firms is characterized by search frictions in the sense of Mortensen and Pissarides (1994). Vacancies and unemployed workers are matched randomly. Existing worker-firm matches are separated at the exogenous rate δ. Following Cairó et al. (2016), after separating from a firm, workers can directly search from unemployment. Therefore, the stock of unemployed workers searching for job interviews is given by

$$\left[\sum_j U_j + \sum_k \sum_i \delta n_k(y_i)\right], \text{ where } j = FT, PT, \; k = VPT, FT, IPT \text{ and } i \in 1, 2,$$

where U_j denotes the stock of unemployed workers, and $n_k(y_i)$ denotes the stock of workers of type k employed at a firm with productivity y_i, both before separations occur. Analogously, there are

$$\sum_k \sum_i \left[(1-\delta) n_k(y_i)\right], \text{ where } k = VPT, FT, IPT \text{ and } i \in 1, 2$$

[31] This is in line with the idea that workers who want to work voluntarily part-time hours cannot work full-time hours because they devote a part of their time e.g. to childcare.

[32] Which is the lower bound of productivity levels for the model to feature an hours and wage ladder. The following results can be generalized to a set-up comprising a continuum of firm productivity.

employed workers searching on-the-job for an interview. The workforce is given by $P = P_{FT} + P_{PT}$, with $P_{FT} = \sum_i [n_{FT}(y_i) + n_{IPT}(y_i)] + U_{FT}$ and $P_{PT} = \sum_i n_{PT}(y_i) + U_{PT}$. The stock of all employed workers with a preference for FT or PT jobs is given by $N_{FT} = \sum_i [n_{FT}(y_i) + n_{IPT}(y_i)]$ and $N_{PT} = \sum_i n_{VPT}(y_i)$, respectively. Unemployed workers search with effort s_u and employed workers with effort s_e for a new job. The aggregate search effort of all worker types is given by

$$L = \left[\sum_j s_u U_j + \sum_j s_e \delta N_j \right], \text{ where } j = FT, PT \text{ and } i \in 1, 2.$$

FT firms post $V_{FT} = \sum_i v_{FT}(y_i)$ and PT firms post $V_{PT} = \sum_i v_{PT}(y_i)$ vacancies. In the aggregate, vacancies are given by

$$V = \sum_j \sum_i v_j(y_i), \text{ where } j = FT, PT \text{ and } i \in 1, 2.$$

Given workers' search effort L and firms' vacancies V, the number of interviews is determined by the following Cobb-Douglas matching technology with matching efficiency ω

$$M = min \left\{ \omega L^{\gamma} V^{1-\gamma}, L, V \right\}, \text{ where } 0 < \gamma < 1 \text{ and } \omega > 0.$$

A firm interviews a worker for a posted vacancy with probability $q = \frac{M}{V}$. An unemployed or employed worker is invited to a job interview with probability $\lambda_u = \frac{s_u M}{L}$ and $\lambda_e = \frac{s_e M}{L}$, respectively. Thus, the probability of an unemployed and employed worker to be interviewed for a job at firm of type $j \in$ FT, PT with productivity $y_i \in y_1, y_2$ is given by $\lambda_u \frac{v_j(y_i)}{V}$ and $\lambda_e \frac{v_j(y_i)}{V}$, respectively.

3.4.2 Surplus

Since I assume random search, there are VPT workers that are matched to FT firms and FT workers that are matched to PT firms. Thus not every interview is successful and leads to a job offer. Only FT workers can work in both firm types, thus the employment status of a worker k uniquely identifies the total surplus of a match. With free entry, it follows that the total match surplus is equal to

$$\begin{aligned} &S_k(y_i) = W_k(w_k(y_i)) - B_j + \Pi_k(w_k(y_i), y_i), \\ &\text{where } j = FT, PT, \ k = VPT, FT, IPT \text{ and } i \in 1, 2, \end{aligned} \tag{3.2}$$

where $W_k(w_k(y_i))$ is the asset value of employment for a worker being paid earnings $w_k(y_i)$, B_j is the value of being unemployed, and $\Pi_k(w_k(y_i), y_i)$ is the value of a filled vacancy for a firm with productivity y_i. Whether a firm-worker match is successful relies crucially on the total match surplus, $S_k(y_i)$. In the following, I assume that both productivity levels are sufficient to generate a positive match surplus for all employment types k.[33]

3.4.3 Wages, Hours and Poaching

While wage posting enables firms to extract the total match surplus when hiring an unemployed worker, the surplus firms can extract from poaching employed workers depends crucially on the total surplus in the incumbent firm. Due to workers' preferences for working hours, two poaching scenarios arise: Firms can poach workers via wages or in the case of IPT employment via longer hours.

Value Function: Unemployment

An unemployed worker can receive a job offer from a PT or FT firm. The worker accepts this offer dependent on each others' type. The value function for an unemployed worker of type $j \in$ PT, FT is given by

$$B_j = b + \frac{1}{1+r}\Big\{\Big(1 - \sum_j \sum_i \lambda_u \frac{\mathbb{1}_j v_j(y_i)}{V}\Big) B_j + \sum_j \sum_i \lambda_u \frac{\mathbb{1}_j v_j(y_i)}{V} \max\Big[W_k(w_k(y_i)), B_j\Big]\Big\}, \tag{3.3}$$

where $r > 0$ is the discount rate and b denotes the unemployment benefits received by a worker.[34] $\mathbb{1}_j$ is an indicator function, with $\mathbb{1}_{FT} = 1$ for all vacancies posted and $\mathbb{1}_{PT} = 1$ if and only if the PT worker meets a firm offering a PT job and zero otherwise. With probability $\lambda v_j(y_i)/V$ an unemployed worker is interviewed by a firm of type j with productivity y_i next period and decides over accepting the job offer and moving to the firm. Otherwise, the unemployed worker does not receive an interview and stays unemployed.

Since wages are posted, $W_k(w_k(y_i)) - B_j = 0$ holds. To attract an unemployed worker, a firm has to pay earnings up the point where the worker is indifferent between both options of moving to the firm and staying unemployed. Thus, the value function for an unemployed worker of type $j \in$ PT, FT can be rewritten as

$$B_j = b + \frac{1}{1+r} B_j \Leftrightarrow B_j = \frac{1+r}{r} b = B. \tag{3.4}$$

It follows that the value of unemployment is the same for all worker types.[35]

[33] A non-negative surplus is sufficient for a match to be successful.

[34] I am interested in long-run effects of selective hiring on workers' job-to-job transition rates and level differences in workers' job mobility, thus I focus on the steady state and drop the time index.

[35] For similar reasons see besides Cairó et al. (2016) also Kudoh et al. (2019).

Poaching by Wages: Workers and Firms

When an employed worker receives an interview at a firm with productivity y' of the same type, the new firm can poach the worker via wages whereas the incumbent firm with productivity y has the possibility to counter this outside offer as specified in Postel-Vinay and Robin (2002).[36] Upon receiving an outside offer from a firm, generating at least as much total surplus as the match with the incumbent firm generates for the worker, the match with the lower surplus firm serves as a threat point, which allows the worker to extract the total lower match surplus from the high surplus firm. Thus, to attract the worker in this situation, a firm has to pay earnings up to the point where the worker is indifferent between both firms. For $k \in$ VPT, FT, IPT three different cases can arise from poaching:

- **Credible Threat (CT):** $S_k(y') \geq W_k(w_k(y)) - B$

  Case 1: Poaching (P) $S_k(y') > S_k(y)$. The worker accepts the poaching offer. The new firm pays earnings $w'_k(y', y)$ such that $W_k(w'_k(y', y)) - B = S_k(y)$.
  Case 2: Bidding (B) $W_k(w_k(y)) - B < S_k(y') < S_k(y)$. The worker has a credible threat of moving to the poaching firm and renegotiates the earnings $w'_k(y, y')$ with the incumbent firm such that $W_k(w'_k(y, y')) - B = S_k(y')$.

- **No Credible Threat:** $S_k(y') < W_k(w_k(y)) - B$

  Case 3: No Bidding (NB). The poaching offer does not generate a credible threat of moving to the new firm and to renegotiate earnings. The firm continues to pay earnings $w_k(y)$.

Keep in mind that there a only two levels of productivity. Thus, workers are only willing to switch to a poaching firm if the incumbent firm is of productivity type y_1 and the poaching of type y_2.

Value Functions: Poaching by Wages

When employed, FT and VPT workers have the possibility of receiving an interview at a new firm of the same type which entails one of the three discussed poaching cases.[37] Thus, the value function for an employed worker in his preferred job type $k \in$ VPT, FT is given by

$$\begin{aligned} W_k(w_k(y), y) = w_k(y) + \frac{1}{1+r}\Big\{\delta B + (1-\delta)\Big[\sum\nolimits_j \sum\nolimits_{y':P} \mathbb{1}_k \lambda_e \frac{v_j(y')}{V} W_k(w'_k(y', y), y') \\ + \sum\nolimits_j \sum\nolimits_{y':B} \mathbb{1}_k \lambda_e \frac{v_j(y')}{V} W_k(w'_k(y, y'), y) \\ + \Big(1 - \sum\nolimits_j \sum\nolimits_{y':CT} \mathbb{1}_k \lambda_e \frac{v_j(y')}{V}\Big) W_k(w_k(y), y)\Big]\Big\}, \end{aligned} \tag{3.5}$$

[36] In this case, poaching is not affected by working hours and identical to the model without IPT employment presented by Cairó et al. (2016).

[37] Recall that PT workers can only work in a firm offering PT hours. Therefore, PT workers can only be poached by PT firms. Furthermore, FT are not willing to switch to PT firms if $S_{FT}(y_1) > S_{PT}(y_2)$. In the model workers employed in their preferred job type cannot be poached by firms offering an unpreferred amount of working hours. As will be shown in Section 3.4.4 this is true for FT workers if $f_{FT}(y_1) > f_{PT}(y_2)$.

where $w_k(y)$ are earnings paid at firm y. $\mathbb{1}_k$ is an indicator function with $\mathbb{1}_k = 1$ if and only if the worker of type k meets a firm of type j offering the preferred job type and zero otherwise. The worker has the possibility of getting interviewed at a firm with productivity y' of the same type as the incumbent firm. If this interview generates a credible threat, either the poaching (P) or bidding (B) case apply, resulting in an earnings adjustment. If the worker does not have a credible threat, the no bidding (NB) case leaves the match unchanged.

For firms matched to workers in their preferred job type, on-the-job search implies that they might lose a worker through poaching. The value of a filled vacancy matching the worker's job preference, i.e. $k \in$ VPT, FT, is given by

$$\begin{aligned}\Pi_k(w(y), y) = f_k(y) - w_k(y) + \frac{1}{1+r}\Big\{\delta 0 + (1-\delta)\Big[\sum\nolimits_j \sum\nolimits_{y':P} \mathbb{1}_k \lambda_e \frac{v_j(y')}{V} 0 \\ + \sum\nolimits_j \sum\nolimits_{y':B} \mathbb{1}_k \lambda_e \frac{v_j(y')}{V} \Pi_k(w_k'(y, y'), y) \\ + \left(1 - \sum\nolimits_j \sum\nolimits_{y':CT} \mathbb{1}_k \lambda_e \frac{v_j(y')}{V}\right) \Pi_k(w_k(y), y)\Big]\Big\},\end{aligned} \tag{3.6}$$

where $f_k(y)$ denotes the output produced from the match. If the worker receives a job offer from a higher surplus firm of the same job type, the worker accepts the poaching offer (P) and leaves the incumbent firm. Additionally, if a worker has a credible threat of leaving, firms have to offer higher wages to keep the worker and thus earnings are renegotiated (B). Otherwise, the match remains unchanged (NB).

Poaching by Hours: Workers and Firms

Besides poaching via wages, when meeting a PT firm, IPT workers can also be poached via hours by FT firms. If an IPT worker meets a FT firm with productivity y', the new firm can poach this worker via hours whereas the incumbent firm has the possibility to counter the offer from the poaching firm via wages as specified in Postel-Vinay and Robin (2002). Whether the worker can be poached by the new firm or renegotiates wages with the incumbent firm is determined by the respective total match surpluses.[38] Three different cases can arise from this poaching situation:

- **Credible Threat (CT):** $S_{FT}(y') \geq W_{IPT}(w_{IPT}(y)) - B$

  Case 1: Poaching (P) $S_{FT}(y') > S_{IPT}(y)$. The worker accepts the poaching offer from the new firm y', which dissolves the work hours mismatch, and the worker becomes a full-time worker. The new firm pays earnings $w'_{FT}(y', y)$ such that $W_{FT}(w'_{FT}(y', y)) - B = S_{IPT}(y)$.

[38] I do not include disutility of labor since it would not affect the mechanism but would also require the inclusion of positive effects of FT positions with regard to benefit coverage and work conditions for the sake of completeness.

Case 2: Bidding (B) $W_{IPT}(w_{IPT}(y)) - B < S_{FT}(y') < S_{IPT}(y)$. The worker has a credible threat of moving to the poaching firm and renegotiates the earnings $w'_{IPT}(y, y')$ with the incumbent firm up to the point where $W_{IPT}(w'_{IPT}(y, y')) - B = S_{FT}(y')$.

- **No Credible Threat:** $S_{FT}(y') < W_{IPT}(w_{IPT}(y)) - B$

  Case 3: No Bidding (NB). The poaching offer does not generate a credible threat of moving to the new firm and to renegotiate earnings. The firm continues to pay earnings $w_{IPT}(y)$.

Taken together, if the interview generates a credible threat, the job offer results in an earnings adjustment and the worker is made better of by deciding in favor of the firm offering the higher total match surplus. It follows that IPT workers are also willing to switch to a FT firm with the same or a lower productivity level as long as $S_{FT}(y') > S_{IPT}(y)$ holds.

Value Functions: Poaching by Wages and Hours

IPT workers have an additional employment option as they can also be poached via longer hours and move to a firm of a different job type. Therefore, the value function of workers with a preference for FT positions employed in unpreferred jobs, i.e. $k = IPT$, differs from unrestricted workers and is given by

$$\begin{aligned} W_k(w_k(y), y) = w_k(y) + \frac{1}{1+r}\Big\{\delta B + (1-\delta)\Big[\sum_j \sum\nolimits_{y':P_j} \frac{v_j(y')}{V} W_j(w'_j(y', y), y') \\ + \sum_j \sum\nolimits_{y':B_j} \lambda_e \frac{v_j(y')}{V} W_k(w'_k(y, y'), y) \\ + \Big(1 - \sum_j \sum\nolimits_{y':CT_j} \lambda_e \frac{v_j(y')}{V}\Big) W_k(w_k(y), y)\Big]\Big\}. \end{aligned} \tag{3.7}$$

Upon receiving an offer from a PT or a FT firm, the worker can switch to the PT firm and stay involuntarily PT employed or move to the FT firm which resolves the work hours mismatch. If the worker meets a PT firm on-the-job, i.e. $j = PT$, one of the three wage poaching cases arises. In contrast, a match with a FT firm, i.e. $j = FT$, entails one of the three hours poaching cases.

Considering the three wage as well as hours poaching cases, the value of a vacancy filled by an IPT worker, i.e. $k = IPT$, is given by

$$\begin{aligned} \Pi_k(w_k(y), y) = f_k(y) - w_k(y) + \frac{1}{1+r}\Big\{\delta 0 + (1-\delta)\Big[\sum_j \sum\nolimits_{y':P_j} \lambda_e \frac{v_j(y')}{V} 0 \\ + \sum_j \sum\nolimits_{B_j} \lambda_e \frac{v_j(y')}{V} \Pi_k(w'_k(y, y'), y) \\ + \Big(1 - \sum_j \sum\nolimits_{y':CT_j} \lambda_e \frac{v_j(y)}{V}\Big) \Pi_k(w_k(y), y)\Big]\Big\}. \end{aligned} \tag{3.8}$$

When a PT firm is matched to a worker with a preference for FT positions, the worker cannot only be poached by other PT firms but also via hours by FT firms. If the worker receives a job offer from a PT firm, i.e. $j = PT$, one of the three wage poaching cases arises. Additionally, if the worker receives an offer from a FT firm, i.e. $j = FT$, one of the three hours poaching cases arises.

3.4.4 Vacancies

Firms can post vacancies $v_j(y)$ at convex costs $c(v_j(y))$, which results in $qv_j(y)$ job interviews. Thus the vacancy posting problem of FT firms is given by

$$\begin{aligned}\max_{v_{FT}(y)} \Big\{ - c(v_{FT}(y)) + qv_{FT}(y)\Big(&\frac{\lambda_u\,[U_{FT} + \delta N_{FT}]}{M} \max\{S_{FT}(y), 0\},\\ &+ \sum_{y'} \frac{(1-\delta)\lambda_e n_{FT}(y')}{M} \max\{\Pi_{FT}(w_{FT}(y, y'), y), 0\}\\ &+ \sum_{y'} \frac{(1-\delta)\lambda_e n_{IPT}(y')}{M} \max\{\Pi_{FT}(w_{FT}(y, y'), y), 0\}\Big)\Big\}.\end{aligned} \tag{3.9}$$

Analogously, the vacancy posting problem of PT firms is given by

$$\begin{aligned}\max_{v_{PT}(y)} \Big\{ - c(v_{PT}(y)) + qv_{PT}(y)\Big(&\frac{\lambda_u\,[U_{PT} + \delta N_{PT}]}{M} \max\{S_{PT}(y), 0\}\\ &+ \frac{\lambda_u\,[U_{FT} + \delta N_{FT}]}{M} \max\{S_{IPT}(y), 0\}\\ &+ \sum_{y'} \frac{(1-\delta)\lambda_e n_{VPT}(y')}{M} \max\{\Pi_{VPT}(w_{VPT}(y, y'), y), 0\}\\ &+ \sum_{y'} \frac{(1-\delta)\lambda_e n_{IPT}(y')}{M} \max\{\Pi_{IPT}(w_{IPT}(y, y'), y), 0\}\Big)\Big\}.\end{aligned} \tag{3.10}$$

Due to the fact that workers with a preference for FT positions are also willing to work in PT firms, an additional value of posting vacancies arises for PT in comparison to FT firms.

The surplus a firm can extract from the match is strongly connected to the employment type of the interviewed worker, i.e. if the worker is hired from unemployment or poached on-the-job. Thus, the expected value of a new match for a FT firm is given by[39]

$$\begin{aligned}J_{FT}(y) = &\frac{\lambda_u\,[U_{FT} + \delta N_{FT}]}{M} \max\{S_{FT}(y), 0\}\\ &+ \sum_{y'} \frac{(1-\delta)\lambda_e n_{FT}(y')}{M} \max\{S_{FT}(y) - S_{FT}(y'), 0\}\\ &+ \sum_{y'} \frac{(1-\delta)\lambda_e n_{IPT}(y')}{M} \max\{S_{FT}(y) - S_{IPT}(y'), 0\}.\end{aligned} \tag{3.11}$$

[39]See B.4 for a detailed derivation. Firms post vacancies such that $c'(v_j(y)) = J_j(y)$ holds.

Analogously, the expected value of a new match for a PT firm is given by[40]

$$
\begin{aligned}
J_{PT}(y) = & \frac{\lambda_u \left[U_{PT} + \delta N_{PT}\right]}{M} \max\{S_{PT}(y), 0\} + \frac{\lambda_u \left[U_{FT} + \delta N_{FT}\right]}{M} \max\{S_{IPT}(y), 0\} \\
& + \sum_{y'} \frac{(1-\delta)\lambda_e n_{VPT}(y')}{M} \max\{S_{VPT}(y) - S_{VPT}(y'), 0\} \\
& + \sum_{y'} \frac{(1-\delta)\lambda_e n_{IPT}(y')}{M} \max\{S_{IPT}(y) - S_{IPT}(y'), 0\}. \qquad (3.12)
\end{aligned}
$$

Equations (3.11) and (3.12) show that the value of a new match depends crucially on all possible match surpluses. To shed light on this result, I rewrite the total match surplus by using the value functions of employed workers, unemployed workers and firms:[41]

$$
\begin{aligned}
S_k(y) &= f_k(y) - b + \frac{1-\delta}{1+r} S_k(y) \\
\Rightarrow S_k(y) &= \frac{1+r}{r+\delta} \left[f_k(y) - b\right]. \qquad (3.13)
\end{aligned}
$$

From the match surplus it follows that the value of a new match, and hence vacancy posting, positively relies on the output produced from the match $f_k(y)$. The output produced from the match is larger in firms with a higher productivity and thus vacancies are increasing in firms' productivity.

3.4.5 Worker Flows

IPT workers can be poached via wages or hours whereas FT workers can only be poached via wages. Therefore, IPT workers have an additional incentive to accept a poaching offer by a FT firm. The job-to-job transition rates from FT to FT and IPT to FT employment, respectively, are given by

$$
\begin{aligned}
p_{FT} &= \frac{1}{\sum_y n_{FT}(y)} \sum_y \sum_{y'} (1-\delta)\lambda_e \frac{v_{FT}(y')}{V} \mathbb{1}\left\{S_{FT}(y') > S_{FT}(y)\right\} n_{FT}(y), \\
p_{IPT} &= \frac{1}{\sum_y n_{IPT}(y)} \sum_y \sum_{y'} (1-\delta)\lambda_e \frac{v_{FT}(y')}{V} \mathbb{1}\left\{S_{FT}(y') > S_{IPT}(y)\right\} n_{IPT}(y),
\end{aligned}
$$

where $\mathbb{1}$ is an indicator functions with $\mathbb{1}\left\{S_{FT}(y') > S_{FT}(y)\right\}$=1 and $\mathbb{1}\left\{S_{FT}(y') > S_{IPT}(y)\right\}$=1 if and only if the total match surplus in the poaching firm exceeds the total match surplus in the incumbent firm and zero otherwise. FT workers only accept an offer from a firm if $S_{FT}(y') > S_{FT}(y)$. From the match surplus, given by Equation (3.13), it follows that FT

[40] See B.4 for a detailed derivation.

[41] See B.3 for a detailed derivation. I assume that a worker poached from a PT firm is as productive as a worker poached from a FT firm or unemployment for FT firms. In the same way, workers poached from a PT firm are as productive as a worker coming from unemployment for PT firms.

workers accept an offer if $f_{FT}(y') > f_{FT}(y)$ and thus if and only if $y' > y$. In contrast, IPT workers accept an offer from a FT firm if $S_{FT}(y') > S_{IPT}(y)$ and thus if $f_{FT}(y') > f_{PT}(y)$.

3.4.6 Effects of Involuntary Part-Time Employment

A wage ladder is a well-established feature of on-the-job search in search and matching models. In line with this result, due to poaching, workers transition to firms with a higher surplus and thus a higher productivity in my model. Therefore, FT and VPT workers move on the wage ladder to higher paying firms via direct job-to-job transitions. This implies that firms with a higher productivity are more successful in poaching workers. By incorporating IPT employment, besides a wage ladder, the model additionally features an hours ladder, which reallocates workers from jobs with short to jobs with long hours, i.e. from PT to FT positions. This result is formalized in Proposition 3.

Proposition 3. *Involuntary part-time employment in the model gives rise to an hours ladder, moving workers from short hours to long hours jobs via direct job-to-job transitions, if there are productivity levels y and y' for which $f_{FT}(y) > f_{PT}(y')$ holds.*

From the job-to-job transition rates it follows that workers' job mobility crucially depends on the relative match surplus. IPT workers are willing to move to a FT firm with a lower or the same productivity than their incumbent PT firm to overcome their work hours mismatch if the output from a match in the FT firm exceeds the output from a match in a PT firm with the same productivity level. Thus, Proposition 4 follows.

Proposition 4. *Involuntary part-time workers accept a wider range of job offers than full-time workers and therefore exhibit a higher rate of job-to-job transitions if $f_{FT}(y) > f_{PT}(y)$.*

Since $f_j(y_i) = A_j y_i$ and $A_{FT} > A_{PT}$ it follows that the output produced from a match in a FT firm always exceeds the output produced from a match in a PT firm with the same productivity level. Therefore, $f_{FT}(y) > f_{PT}(y')$ always holds for the same productivity level, $y = y'$. The assumption that a higher amount of hours worked results in a higher output, i.e. that $A_{FT} > A_{PT}$, is sufficient for the conditions stated in Proposition 3 and 4 to be satisfied. Furthermore, from the assumption that FT workers are not willing to switch to PT firms, i.e. $S_{FT}(y_1) > S_{PT}(y_2)$, it directly follows that IPT workers employed at high productivity PT firms are also willing to switch to low productivity FT firms. Using the fact that the productivity of firms takes on only two values, the job-to-job transition rates simplify to

$$p_{FT} = \underbrace{\frac{n_{FT}(y_1)}{n_{FT}(y_1) + n_{FT}(y_2)}}_{\in[0,1]} \underbrace{(1-\delta)\lambda_e \frac{v_{FT}(y_2)}{V}}_{>0}, \tag{3.14}$$

$$p_{IPT} = \underbrace{(1-\delta)\lambda_e \frac{v_{FT}(y_2)}{V}}_{>0} + \underbrace{(1-\delta)\lambda_e \frac{v_{FT}(y_1)}{V}}_{>0}. \tag{3.15}$$

Since $n_{FT}(y_1)/(n_{FT}(y_1) + n_{FT}(y_2)) \in [0, 1]$, the first term in Equation (3.15) exceeds the term in Equation (3.14). Additionally, FT workers are only willing to move from a low productivity to a high productivity FT firm, whereas IPT workers in a high productivity PT firm are also willing to switch to a low productivity FT firm. This additional channel is summarized in the second term of Equation (3.15), which is absent in p_{FT}. Directly, it can be seen that $p_{IPT} > p_{FT}$ holds and thus that IPT workers move with a higher job-to-job transition rate to FT jobs in comparison to FT workers.[42]

Pace and the Productivity Level

Firms with a higher productivity post more vacancies because they exhibit a higher total match surplus and thereby a higher expected value of a new match, see Equations (3.11) and (3.12). Thus, the pace of the job ladder crucially relies on the labor productivity of firms, A_j. The following Proposition holds.

Proposition 5. *The pace of the wage and hours ladder, moving workers from low wage and short hours jobs to high wage and long hours jobs, is increasing in labor productivity A_j.*

The mechanism behind this result is quite simple. From Equation (3.9) and (3.10) it follows that firms post less vacancies the lower A_j. With an overall drop in firms' labor productivity, also high productivity firms post less vacancies, workers get poached away less frequently and transition rates decline. In line with Cairó et al. (2016), the wage ladder experience a slowdown, with workers moving less frequently to higher paying firms via job-to-job transitions. Additionally, the pace of the hours ladder declines, because IPT workers are poached less often and thus transitions to FT positions are slow.

[42]The rate at which workers move to a new job depends on the search intensity of worker types, which differs between s_e and s_u, following Cairó et al. (2016). Since workers on IPT positions are likely to have more time that they can spend searching for new jobs, I could also have assumed different on-the-job search intensities for FT and IPT workers. This would lead to an even higher search intensity and therefore to a higher job-to-job transition rate for IPT workers in comparison to FT workers. Thus, the results presented here can be interpreted as a lower bound of the effect.

Vacancies and Working Hours

Since the model features undirected search, firms learn about workers' employment preferences, $j \in$ VPT, FT, during the job interview. From Equations (3.11) and (3.12), the values of a new match, it follows that the existence of PT firms affects the vacancy posting behavior of FT firms and vice versa. For the influence of different working hours on FT and PT firms, Proposition 6 follows.

Proposition 6. *Involuntary part-time employment entails a positive effect on part-time vacancies and a negative effect on full-time vacancies if there is a y for which $f_{IPT}(y) > b$ holds.*

As the match surplus is always positive for both productivity levels y_1 and y_2, it holds that $S_k(y) > 0$. Therefore $f_{IPT}(y) > b$ is always true. Due to the fact that two additional sources of hiring arise for PT firms, because they can hire FT workers from unemployment and IPT workers on the job, they cannot be worse of than in the situation without IPT work. Therefore, PT firms post more vacancies because an additional surplus arises from hiring FT and IPT workers. For FT firms, hiring unemployed workers entails the highest match surplus. Thus, the larger the share of unemployed workers, the higher the expected value of a filled vacancy. FT firms would be better of hiring unemployed workers rather than poaching IPT workers because IPT workers exhibit a higher outside option. Since the share of unemployed workers decreases due to IPT work, FT firms post less vacancies.

Employment and Unemployment Rates

By focusing on the steady state, the number of unemployed and employed workers with a preference for FT and PT jobs are constant. Thus, employment and unemployment transitions for both worker types are by definition equal. Entries to employment are given by unemployed workers who have found a job. Entries into unemployment are given by employed workers who were exogenously separated from their job and are not moving back into employment within the same period. The employment and unemployment rates for both worker types are given by[43]

$$\frac{N_{FT}}{P_{FT}} = \frac{\lambda_u}{\lambda_u + \delta(1-\lambda_u)}, \quad \frac{N_{PT}}{P_{PT}} = \frac{\mu_{PT}\lambda_u}{\lambda_u + \delta(1-\mu_{PT}\lambda_u)},$$
$$\frac{U_{FT}}{P_{FT}} = \frac{\delta(1-\lambda_u)}{\lambda_u + \delta(1-\lambda_u)}, \quad \frac{U_{PT}}{P_{PT}} = \frac{\mu_{PT}\delta(1-\lambda_u)}{\lambda_u + \delta(1-\mu_{PT}\lambda_u)},$$

with $\mu_{PT} = \frac{V_{PT}}{V_{PT}+V_{FT}}$. It can be shown, in Proposition 7, that the following relationship between the employment and unemployment rate for workers with a preference for FT and PT jobs holds:

[43] See B.5 for a detailed derivation.

Proposition 7. *Workers with a preference for full-time positions exhibit a higher employment and lower unemployment rate than part-time workers if* $V_{FT} > 0$.

This is due to the fact that workers with a preference for FT jobs accept matches with both firm types, whereas PT workers accept only vacancies from PT firms when unemployed.[44] This result is in line with empirical evidence on FT and PT unemployment rates.[45]

3.5 A Model with Involuntary Part-Time Employment and Selective Hiring

Building on the empirical evidence presented in Section 3.3, I will now turn to the analysis of the strong decrease in the job-to-job transition rate for workers out of IPT employment. Therefore, I extend the wage and hours ladder model formalized in Section 3.4 to explore a potential mechanism behind the reported divergence of trends in job-to-job transition rates. I propose a channel focusing on the interaction between recruitment and a scarring effect of IPT work.

Selective Hiring of Job Applicants

Motivated by the empirical evidence on a scarring effect of IPT employment, I incorporate selective hiring of firms in the model. In the model, selective hiring means that FT firms are only willing to hire workers who are already employed in FT rather than PT positions.[46] I assume that a fraction s of vacancies are filled this way and thus I incorporate selective hiring in the model by assuming exogenously that matches are not sustainable if the employment history of a worker does not match the vacancy requirements.[47] It follows that after observing a workers' current employment type in the job interview, firms screen out IPT workers when recruiting selectively and the match is not realized. Upon matching with a FT firm on-the-job, FT workers can move to a random vacancy, while IPT workers are only able to resolve their working hours mismatch when interviewed for a non-selective vacancy. An IPT worker is screened out when interviewed on-the-job by a poaching FT firm with probability $\lambda_e \frac{V_{FT}^s}{V}$, where $V_{FT}^s = s \sum_i v_{FT}(y_i)$ gives the number of selective vacancies posted by FT firms. Therefore, not all workers with a preference for FT positions are recruited after being interviewed by FT firms.

[44] See B.5 for a detailed proof.

[45] Buffie (2016) reports an average unemployment rate from 1994 to 2007 of 4.9% for FT workers and 6.7% for PT workers.

[46] This is in line with the idea of screening unemployed workers presented in Eriksson and Gottfries (2005) and Ravenna and Walsh (2012).

[47] As clarifying the source of selective hiring is left for future research but endogenizing s would lead to strong normative implications, I take s as exogenously given. For a detailed discussion of possible effects see Section 3.6.

3.5.1 Vacancies

As before, firms can post vacancies $v_j(y)$ at convex costs $c(v_j(y))$, which results in $qv_j(y)$ job interviews. With selective hiring, the vacancy posting problem of a FT firm becomes[48]

$$\begin{aligned}\max_{v_{FT}(y)}\Big\{ &- c(v_{FT}(y)) + qv_{FT}(y)\Big(\frac{\lambda_u\left[U_{FT}+\delta N_{FT}\right]}{M}\max\{S_{FT}(y),0\}\\ &+\sum_{y'}\frac{(1-\delta)\lambda_e n_{FT}(y')}{M}\max\{\Pi_{FT}(w_{FT}(y,y'),y),0\}\\ &+\sum_{y'}\frac{(1-\delta)\lambda_e(1-s)n_{IPT}(y')}{M}\max\{\Pi_{FT}(w^s_{FT}(y,y'),y),0\}\Big)\Big\}.\end{aligned} \tag{3.16}$$

Due to selective hiring, a match with a IPT worker is realized if the vacancy is filled non-selectively, which is the case for a fraction of $(1-s)$ vacancies. Thus, the expected value of a new match for a FT firm with selective hiring becomes[49]

$$J_{FT}(y) = \frac{\lambda_u\left[U_{FT}+\delta N_{FT}\right]}{M}\max\{S_{FT}(y),0\} \tag{3.17}$$

$$+\sum_{y'}\frac{(1-\delta)\lambda_e n_{FT}(y')}{M}\max\{S_{FT}(y)-S_{FT}(y'),0\}$$

$$+\sum_{y'}\frac{(1-\delta)\lambda_e(1-s)n_{IPT}(y')}{M}\max\{S_{FT}(y)-S_{IPT}(y'),0\}. \tag{3.18}$$

It follows that the existence of selective hiring affects the vacancy posting behavior of FT firms. From the expected value of a new match for a FT firm with selective hiring, given by Equation (3.18), Proposition 8 follows:

Proposition 8. *Selective hiring entails a negative effect on full-time vacancies if there are y and y' for which $f_{FT}(y) > f_{IPT}(y')$ holds.*

As $f_{FT}(y) > f_{IPT}(y)$ holds, the condition stated in Proposition 8 is always true. As long as a positive surplus arises from poaching a IPT worker, selective hiring adversely affects the expected value of a new match for FT firms. Since firms post vacancies such that $c'(v_{FT}(y)) = J_{FT}(y)$ holds, selective hiring leads to a negative effect of FT vacancies. The larger the share of selective vacancies, the lower the expected value of a filled vacancy and thus the stronger the adverse effect on FT vacancies. From Proposition 8 it follows that not only IPT workers are affected by selective hiring but also FT workers through the indirect vacancy channel.

[48]The surplus is still given by $S_{FT}(y) = \frac{1+r}{r+\delta}\left[f_{FT}(y)-b\right]$. See B.6 for a detailed derivation.

[49]The vacancy posting problem and the expected value of a match for PT firms is not affected by selective hiring.

3.5.2 Effects of Selective Hiring

Due to selective hiring, IPT workers are only poached if the vacancy is filled non-selectively, whereas FT workers can be poached when meeting with a random FT vacancy. Therefore, the job-to-job transition rates from IPT to FT employment changes to

$$p_{IPT} = \frac{1}{\sum_y n_{IPT}(y)} \sum_y \sum_{y'} (1-\delta)\lambda_e(1-s)\frac{v_{FT}(y')}{V} \mathbb{1}\left\{S_{FT}(y') > S_{IPT}(y)\right\} n_{IPT}(y),$$

which can again be simplified to

$$p_{IPT} = (1-\delta)\lambda_e(1-s)\frac{v_{FT}(y_1) + v_{FT}(y_2)}{V}. \tag{3.19}$$

While FT workers can still switch to all FT firms, selective hiring has a negative direct effect on the job-to-job transition rate of IPT workers. This can be seen from Equation (3.19), where p_{IPT} depends negatively on the selective hiring share s. Incorporating selective hiring in the model leads to the following result formalized in Proposition 9:

Proposition 9. *Selective hiring entails a negative scarring effect of involuntary part-time employment on workers' employment opportunities and thus on the job-to-job transition rate from involuntary part-time to full-time positions. The effect is increasing in the selective hiring share s.*

The idea behind this mechanism is quite simple: When interviewing workers, firms learn about their current employment types. A fraction s of vacancies is not filled with IPT workers. When interviewed for a selective vacancy, despite the fact that IPT workers are willing to move to the FT firm, the match is not realized and the worker is left with the IPT job. The employment opportunities of IPT workers and accordingly the size of the scarring effect crucially depends on the degree of selective hiring in the model. The higher the share s, the lower is the probability of IPT workers to find a FT job and to resolve their work hours mismatch. Furthermore, both IPT and FT workers are affected by the negative indirect effect of selective hiring on FT vacancies.

Taken together, I extended the hours ladder model, derived in Section 3.4, to examine the interaction between firms' recruitment and workers' job mobility. By introducing selective hiring in the model, IPT workers are screened out during the job interview, finding a FT position becomes harder, and the transition to FT jobs is slow. It follows that a higher degree of selective hiring in the model leads to a drop in the job-to-job transition rate from IPT to FT positions.

3.6 Discussion

It is well known that IPT employment has a sizeable impact on workers' income and work conditions. By deteriorating workers' employment opportunities, scarring of IPT workers leads to additional costs of IPT employment, which are neglected in the literature.[50] My results provide a starting point for discussing appropriate policies targeted to reduce the cost of IPT employment and enhance workers' job mobility and opportunities.[51] The identification of such policy measures depends crucially on the reasons for selective hiring, i.e. why episodes of IPT employment are relevant for firms when recruiting. In the following, I briefly go through policies for three possible sources: a loss of human capital during IPT employment, a simple discrimination effect of firms, and an identification problem of applicants' PT types.

Scarring of IPT workers may results from skill detoriation during IPT employment, and thus firms prefer to hire FT over IPT workers.[52] Important factors in explaining a skill loss from IPT employment can be the lower amount of hours worked, a lower degree of training on-the-job, or a lower chance to be chosen for on-the-job training programs, which could result in a skill loss as large as the loss from unemployment. Thus, policies proposed to alleviate the skill loss from unemployment may be applicable to IPT employment as well. A frequently proposed measure is a retraining subsidy for unemployed workers, which could be extended to provide support for IPT workers.

The scarring effect could also be driven by simple signaling channels, such as discrimination or differentiation effects. A discrimination effect of firms, resulting in a stigma of IPT employment, can be mitigated by extending existing anti-discrimination laws. The existing laws aim to prohibit discrimination against job applicants with regard to a wide range of characteristics, such as race, color, sex, and age.[53] In contrast, the differentiation effect means that firms' are unable to identify a worker's PT type, resulting in a scarring effect if firms avoid to recruit VPT workers for FT positions. Since VPT workers choose shorter hours in their current jobs, this differentiation effect could be driven by firms' uncertainty over workers' actual preferences or motivation for working in FT positions and thus by firms' perceptions over VPT workers. To mitigate these effects, polices could be targeted to simplify and improve the screening process of job applicants.

Since the relative importance of the discussed factors is not clarified but the proposed policies are only suitable for the respective channels, avoiding IPT employment in the first place could prevent negative long-term employment effects regardless of the underlying mechanism. This is in line with proposed policies for unemployed workers, which are mostly targeted to support employment rather than mitigate consequences for workers.[54] Since IPT workers are willing to

[50] Especially, when considering recessional effects on the labor market, the increased use of IPT employment entails negative long term employment effects for workers.

[51] With regard to overall job mobility, Mussida and Zanin (2020) recommend the investment in local programmes, providing services to assess skills and interests, job search assistance, and training for occupational skills, to encourage workers' overall job mobility.

[52] This is in line with the extensive evidence that workers lose a part of their human capital during unemployment. See, for example, Pissarides (1992).

[53] These laws are enforced by the U.S. Equal Employment Opportunity Commission (EEO).

[54] Arulampalam (2001) suggests to directly enhance employment by in-work benefits, which should be time limited to preserve workers incentives for skill acquisition. Coles and Masters (2000) find that policies targeted towards prevention are effective in mitigating long-term unemployment effects. They show that vacancy

work in FT positions, vacancy subsidies proposed to prevent unemployment could be refined by targeting especially FT positions. With regard to unemployment policies, these FT vacancy subsidies could also be more effective than non-restrictive subsidies. In line with Pedulla (2016), my findings also suggest that not every job is preferable over being unemployment. IPT positions cannot necessarily be used as stepping stone jobs, therefore policies should not only aim to bring unemployed workers back to employment but also back to jobs offering further employment opportunities.

3.7 Conclusion

In this paper, I document both empirically and analytically a connection between IPT employment and workers' job mobility in the U.S. To do so, I provide empirical facts about differences in the development and stocks of job-to-job transition rates between worker types. To find FT employment, IPT workers transition on average more often to new jobs than unrestricted workers. The job mobility of IPT workers is characterized by a particularly strong trend decline over the last two decades. While, the job-to-job transition rates have been declining persistently for all types of workers, the job-to-job transition rate from IPT to FT dropped by around 55% in comparison to around 30% for all other worker types. I connect this pattern to changes in firms' hiring behavior. When firms incorporate informations over workers' employment histories in their recruitment decision, they prefer to hire FT workers and screen out IPT workers. I present evidence that histories of IPT employment have become more relevant for firms when recruiting and thus that vacancies have been filled more selectively over time.

To illustrate this mechanism, I introduce IPT employment and selective hiring of firms in a search and matching model with on-the-job search, in which IPT employment generates an hours ladder and job opportunities are shaped by a worker's current employment status. In line with the empirical evidence presented in this paper, IPT workers move more frequently to new jobs than workers who retain their employment status and who are not affected by mismatch between actual and desired work hours. This is because IPT workers are willing to accept a wider range of job offers for working the desired number of hours. When a worker's current employment status matter, and firms hire selectively, having worked PT leads to a scarring effect on workers' employment opportunities. Thus, by introducing selective hiring in the model, it becomes harder for IPT workers to move to FT employment. Workers' employment opportunities and, accordingly, also the size of the scarring effect crucially depends on the degree of selective hiring in the model. A higher degree of selective hiring results in a lower pace of workers' job-to-job transitions from IPT to FT positions.

With regard to workers' overall job mobility, the Council of Economic Advisers (2016) reports that declining labor market dynamism has led to an increasing ability of employers to exercise wage-setting power in recent decades. They argue that this increase in firms' wage-setting

creation subsidies are preferable over retraining subsidies.

power can lead to a reduction in wages, employment, and overall welfare. The results reported in my paper suggest to revisit both, the welfare implications of the drop in workers' job mobility by considering different employment statuses and the welfare implications of IPT employment by incorporating the influence on workers' job mobility. Policy measures are likely to entail a positive effect on workers' job mobility when targeted to prevent IPT employment, which could have far-reaching welfare effects. Thus, my findings suggest to alter the focus of the ongoing policy debate on encouraging workers' job mobility by connecting it to issues of IPT employment.

4 Outlawed: Estimating the Labor Market Effects of Judicial Ideology

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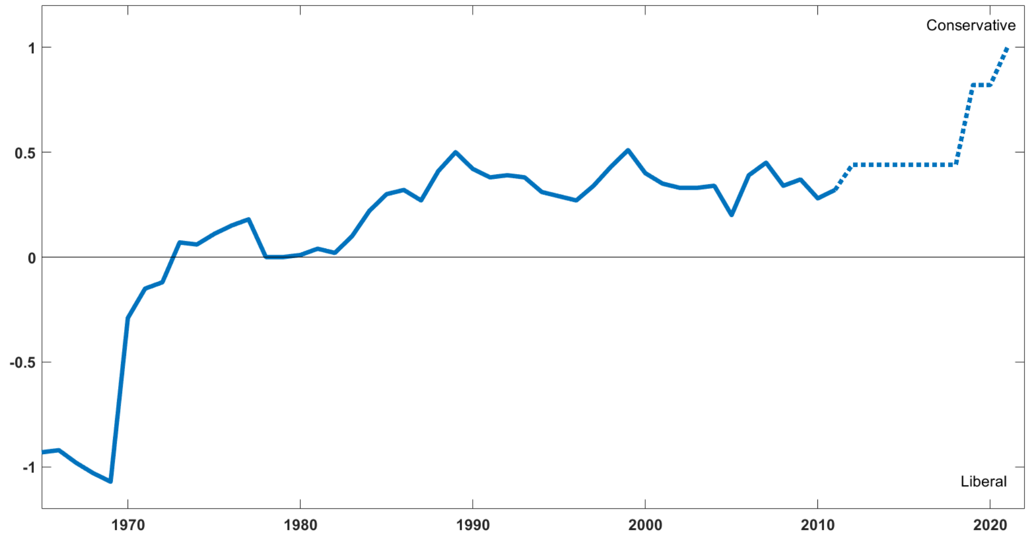
4.1 Introduction

Do ideological tendencies influence court rulings? An exhaustive literature suggests that the answer to this question is: Yes! (cf. Cohen and Yang, 2019; Taha, 2004; Songer et al., 1994). However, do general ideological tendencies of the judiciary also have direct economic effects? And if yes, how large are these? In this paper, we aim to fill a gap in the literature by providing answers to these important questions.

Ideological tendencies of the judiciary are generally considered to be of paramount importance in the United States and Supreme Court nominations are perceived to be among the most important decisions of a U.S. president. The confirmation battles regarding President Trump's Supreme Court nominees in the U.S. Senate corroborate this view. With Supreme Court justices serving on average for 16 years, and several justices having served twice as long, the appointment of a Supreme Court justice possibly influences society long after the appointing president has departed from office. Unsurprisingly, the appointment of conservative federal judges has been one of most prominent topics in both of Donald Trump's presidential campaigns and one of the major appeals to moderate Republicans.

As reported in Figure 4.1, over the past 50 years, the U.S. Supreme Court has shifted strongly to the right. President Trump's nominations of Brett Kavanaugh and Amey Comey Barret and their confirmations in the Senate shifted the Court further to the right, changing the median justice from Justice Anthony Kenney to Chief Justice John Roberts and then from Roberts to Justice Neil Gorsuch. In 2021, the Court is probably the most conservative on record. In this paper, we examine how the ideological composition of the Supreme Court affects the life of American households. While no small share of the public debate about the consequences of Supreme Court ideology discusses abortion, guns, civil rights, and voting, we focus on the economic consequences of changes in Supreme Court ideology. To this end, we analyze a data set which is representative for the U.S. population. This distinguishes our paper from existing evidence on the economic impact of the Supreme Court which is either case-based or purely anecdotal (cf. Epstein et al., 2013; Gilman, 2014).

Figure 4.1. Ideological Leanings of the U.S. Supreme Court



Note: This graph depicts the ideal point estimates provided in the dataset by Bailey (2013) for the ideological leanings of the median Supreme Court justice between 1965 and 2011. The estimates from Bailey (2013) are chosen over the estimates from Martin and Quinn (2002), as the former estimates explicitly take into account the issue of agenda changes over time by using bridging information, see Section 4.3. This allows for the use of the scores in a cardinal sense, whereas the estimates in Martin and Quinn (2002) can only be used as ordinal measures. However, both estimates clearly show the shifts in ideological leanings of the Supreme Court towards the conservative end of the ideological spectrum since the 1970s. As the Bailey scores are only available until 2011, we estimate potential scores for the years 2012 to 2020 based on the median justice according to the estimates from Martin and Quinn (2002) and the mean Bailey score of this justice. The median justice from 2012 to 2018 has been Justice Kennedy and the median justice in 2019 and 2020 – after the retirement of Justice Kennedy and the appointment of Justice Kavanaugh by President Trump – has been Chief Justice Roberts. The potential ideology score for the year 2021 is calculated based on Epstein et al. (2016) and Judicial Common Space scores (cf. Epstein et al., 2007), both of which – assuming the confirmation of Amy Coney Barret as successor of Justice Ginsburg – place the likely median justice for the next terms, Neil Gorsuch, ideologically very close to Justice Alito.

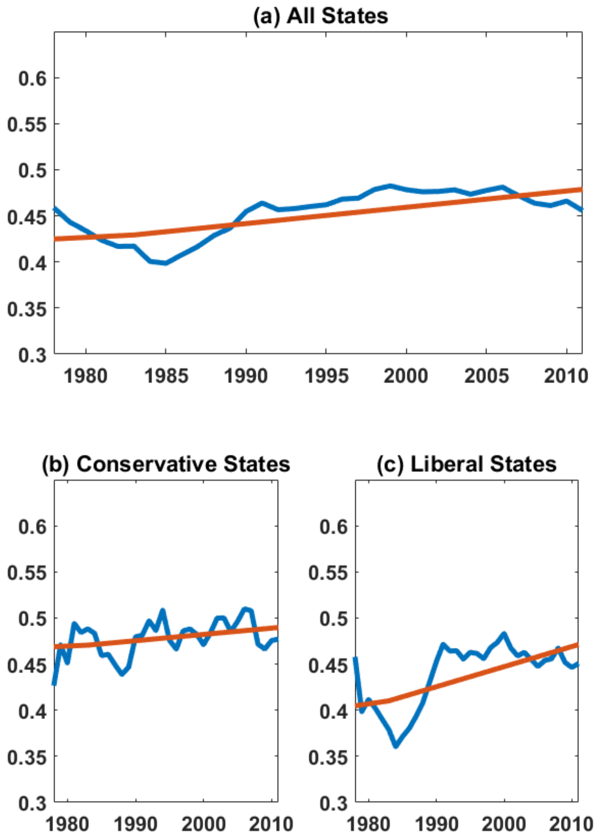
Our identification strategy exploits variation across U.S. states in how strongly jurisprudence in a state is affected by ideological changes at the Supreme Court. Courts within a state, and in particular federal district courts, are important for the economy of this state because the Supreme Court only hear about 150 cases every year and the decisions made by federal courts therefore constitute the last word in thousands of cases every year. A large literature (cf. Boyd, 2015a; Benesh and Reddick, 2002; Cannon and Johnson, 1984; Wasby, 1970; Songer et al., 1994) establishes that lower courts tend to follow the path set by the Supreme Court when the Supreme Court's orientation is clear and unambiguous, whereas an ideologically rather neutral or ambiguous approach of the Supreme Court gives judges some leeway which they can use to follow their own ideology. This behavior of judges is usually attributed to reversal aversion (cf. Miceli and Coşgel, 1994; Posner, 2005; Gennaioli and Shleifer, 2008; Randazzo, 2008). Building on Miceli and Coşgel (1994), we develop a model of judge decision-making with ideological preferences and reversal aversion that makes this argument explicit. The model predicts that a state is more strongly affected by the changes in Supreme Court ideology since the late 1970s (from center to clearly conservative, see Figure 4.1) the more liberal its district court judges are. The intuition is as follows. In the late 1970s, with the Supreme Court rather balanced ideologically, both more conservative and more liberal district court judges were, at least partly, able to influence court rulings according to their own ideology. With the Supreme Court shifting towards being more conservative, all district courts issue rather conservative rulings. While rulings in conservative districts remain rather conservative, liberal judges shy away from the risk of reputational damage due to overturned rulings by also issuing more conservative rulings.

We confirm the predicted regional heterogeneity in the effects of Supreme Court ideology on decisions by lower courts using an econometric procedure derived from the model. To this end, we use data on rulings of federal district courts in close to 24,000 economic or labor-related cases from the Carp-Manning U.S. District Court Database compiled by Carp and Manning (2016). District court rulings are chosen because of three reasons. First, the federal court system hears cases involving the laws and treaties of the U.S. Hence, a large share of lawsuits related to economic issues are filed in federal courts, while the state courts are mostly concerned with traffic cases, which account for over 50% of their caseload. Specifically, according to Clermont and Schwab (2009), employment cases have constituted the largest single category of federal civil cases up to 2001, accounting for nearly 10% of the total federal caseload. In contrast, employment cases only account for less than 0.2% of the total caseload of state courts according to the 1992 Civil Justice Survey of the State Courts. Second, rulings issued by the district courts are much more likely to create a precedent than rulings at state courts and are thus relevant to a large number of additional cases. Third, district courts have the last word in about 99% of the filed federal court cases, as only about 1% of all district court cases are reversed by higher courts (cf. Cohen and Yang, 2019; Edwards, 2019; Eisenberg, 2004).

We find that an increase in conservatism at the Supreme Court, in line with our model, strongly and significantly increases the share of conservative rulings in states with rather liberal district courts relative to the rulings in states with rather conservative district courts. A clear first indication of this finding is provided in Figure 4.2, which depicts the evolution of the share of conservative rulings in U.S. district courts. While there has been an increase in the share of conservative rulings both in states with rather liberal and in states with rather conservative district courts between 1978 and 2011, this increase has been, in line with our prediction, much more pronounced in states with liberal district courts.

Moving beyond descriptive evidence, we establish that an interaction term between Supreme Court ideology and district court ideology is able to capture exogenous variations in district court rulings along the ideological spectrum. Borrowing methodology from the trade and migration literatures, where researchers exploit regional variation in the exposure to import competition (cf. Autor et al., 2013) or migrant inflows (cf. Dustmann et al., 2017) to identify causal effects of these phenomena, we use this interaction term to analyze the effect of court rulings on the labor market. Specifically, we use an interaction term between time-varying Supreme Court ideology and a time-invariant state-specific measure of the ideology of district

Figure 4.2. Share of Conservative District Court Rulings in Economic and/or Labor Cases



Note: This graphs depicts the five-year moving average of the share of conservative rulings for cases in the Economic and/or Labor Cases category in the Carp-Manning U.S. District Court Database compiled by Carp and Manning (2016) for all states, for states with conservative district courts ($dci_s > 0$), and for states with liberal district courts ($dci_s < 0$). The orange lines are linear trends.

court judges in regressions of labor market outcomes that include both time and state fixed effects.[1] This exploits that court rulings in more liberal states are more strongly affected by the Supreme Court's rising conservatism, such that the coefficient on the interaction term is to be interpreted as a causal effect of ideological tendencies of the judiciary. Put differently, the econometric procedure isolates the part of the change in regional district court rulings that is driven by developments at the U.S. Supreme Court in Washington D.C. and therefore arguably exogenous to regional labor market conditions.

[1]We focus on labor market outcomes as labor earnings are the major source of income for most households and thus a primary determinant of life satisfaction. With more conservative judges and justices tending to be rather pro-business and more liberal judges rather pro-worker, ideological shifts in Supreme Court composition affect decisions in cases regarding affirmative action, union rights, worker compensation upon firings, layoffs, and the like. The Business Litigant Dataset for the terms between 1946 and 2011 and the fraction of votes in favor of business in Epstein et al. (2013) reveal large effects of changes in Supreme Court composition on rulings, especially for cases concerning economic issues. Seven of the ten Supreme Court justices least favorable to businesses served between 1960 to 1970. In contrast, in 2011 five of the nine serving Supreme Court justices counted among the ten justices most favorable to businesses.

Our empirical analysis suggests that an increase in the share of pro-business rulings at district courts increases labor market fluidity. Unemployment falls, while the job-finding rate and employment increase. However, on the downside, we find that more pro-business rulings tend to reduce wages and other measures of job quality while accelerating the hollowing-out of the middle class, as union coverage and employment shares in routine-intensive occupations and industries fall. Moreover, we also find that conservative court rulings contribute to increasing income inequality. Quantitatively, a ten percentage point increase in the share of pro-business rulings in a state is associated with a reduction in the state's unemployment rate by about 0.7 percentage points relative to other states. Average hourly wages fall by 1.7%, union coverage by 1.3 percentage points, and the employment share in routine-intensive occupations by 0.6 percentage points. Income inequality, measured as the 90/10 ratio in family income, increases by 3.7%.

Over the 34 years in our sample, the Supreme Court ideology shifted by +0.4 points. We construct a thought experiment in order to gauge the quantitative meaning of our results. Assuming that the state with the most conservative district court judges is unaffected by the rightward shift of the Supreme Court, we show that the conservative shift in Supreme Court ideology approximately accounted for an increase of 18.5 percentage points in the share of pro-business rulings at district courts, a decrease of about 1 percentage point in the unemployment rate, 3 percentage points in the average hourly wage rate, 2.5 percentage points in union coverage and 1 percentage point in the routine employment share, as well as an increase of 6 percentage points in the 90/10 income ratio. In this light, increasing judicial conservatism seems to have contributed to important long-run economic developments such as wage stagnation, deunionization, job market polarization, and rising inequality.

Our main empirical results can be rationalized in a simple search and matching framework which we extend by wrongful-termination lawsuits upon separation. In the model, a larger share of pro-business rulings induces falling wages by eroding the bargaining power of workers. Lower labor costs result in a larger number of posted vacancies and consequently in a higher job-finding rate and lower unemployment rate. These theoretical results provide a clear indication that the threat of wrongful termination lawsuits is a promising driver of our empirical findings.

Our results have important implications regarding the appointment and retirement of federal judges. Due to lifetime appointments and increasingly strategic retirements on federal courts, changing an established majority in the judiciary has become ever more difficult over the last decades. This means that today's decisions regarding the composition of the judiciary influence peoples' lives for decades to come, even though future generations might have very different preferences regarding societal trade-offs, especially when taking into consideration the rapidly changing composition of the U.S. population. Given that our results reveal quite strong effects of judicial ideology, they lend support to term limits for federal judges, as they are proposed by politicians from both sides of the aisle.[2]

[2]Prominent advocates include Senators Sanders, Warren, Bennet, Rubio, and Cruz.

The remainder of the paper is organized as follows. In Section 4.2 we give an overview of the related literature. The effect of Supreme Court ideology on district court rulings is discussed and estimated in Section 4.3. The effect of ideological tendencies of the judiciary on the labor market is estimated in Section 4.4. The results are summarized in Section 4.5.

4.2 Related Literature

This paper is related to different strands of the literature, in particular to those analyzing the determinants of labor market outcomes and of court rulings, respectively.

A number of important determinants of labor market fluidity have been identified by the literature. For example, firing costs have been shown to reduce job-finding rates both theoretically (cf. Wasmer, 2006) and in the data (cf. Kugler and Saint-Paul, 2004). Kugler and Saint-Paul (2004) and Autor et al. (2006a) document that exceptions to the employment at-will doctrine (wrongful-discharge laws) reduce job-creation and lead to lower employment rates. Acemoglu et al. (2001), among others, illustrate that employment protection laws reduce the job-finding probability for affected groups. Cahuc et al. (2019) show that a pro-worker ruling in a wrongful-termination case reduces job-creation in the affected firm. We contribute to this field by emphasizing that increasingly conservative court rulings in economic cases increase both the employment rate and the job-finding rate – not only in individual firms that have been on the losing end of a wrongful-termination lawsuit but in the overall economy.

We also contribute to the debate about the causes of incisive developments witnessed over the last decades: computerization, skill-biased technical change, and routine-biased technical change are put forward as explanations for rising inequality (cf. Autor et al., 2006c), structural change away from manufacturing industries (cf. Autor et al., 2003), polarizing changes in the occupational employment structure at the expense of routine-intensive jobs (cf. Autor and Dorn, 2013), and deunionization (cf. Dinlersoz and Greenwood, 2016). Our results complement these explanations by showing that increasing conservatism of the judiciary accelerates all of these developments.

Economic literature going beyond the affected parties in a particular court ruling is rare. Analyzing case composition, rulings, and votes of Supreme Court justices over time, Epstein et al. (2013) conclude that the Supreme Court has indeed become more favorable to businesses over the last decades. The analysis does however not extend to the effect of the larger share of pro-business rulings on actual economic conditions. Gilman (2014) argues that the Supreme Court reinforces economic inequality by verbally analyzing selected Supreme Court rulings. Neither Epstein et al. (2013) nor Gilman (2014) provide a systematic statistical evaluation of the economic impact of the Supreme Court.

Due to our identification of exogenous variation in court rulings, our paper is also related to the literature that discusses determinants of court rulings which are not directly related to the case at hand. This literature has established that court rulings, conditional on case characteristics, depend on aggregate conditions such as outside temperatures (cf. Heyes and Saberian, 2019), media coverage on crime (cf. Philippe and Ouss, 2018), the success of local sports teams (cf. Eren and Mocan, 2018), and the aggregate business cycle (cf. Ichino et al., 2003; Marinescu, 2011). Furthermore, there is ample evidence that, conditional on case characteristics, individual characteristics of judges at various levels of the judiciary have substantial effects on court rulings. These studies exploit the random case assignment of heterogeneous judges to identify the effects of criminal sentencing (cf. Kling, 2006; Aizer and Doyle Jr., 2015; Dobbie et al., 2018), disability payments (cf. Dahl et al., 2014; French and Song, 2014), firing costs (cf. Cahuc et al., 2019), judge gender (cf. Boyd et al., 2010; Knepper, 2017), and judge race (cf. Kastellec, 2013; Yang, 2015). The ideology or political affiliation of judges is an exceptionally important determinant of rulings. While this is undisputed for U.S. Supreme Court justices, empirical studies also emphasizes an important role of ideology in the lower courts, including the federal district courts on which our analysis focuses (cf. Taha, 2004; Cohen and Yang, 2019).

A number of studies have addressed the interplay between a judge's own ideological preferences and the preferences of the judge's superiors at higher courts, which is at the core of our identification strategy. In particular, judges are generally considered to be reversal-averse which lets them put their own ideological preferences last when these stand in sufficiently strong conflict with the ideologies of their superiors at higher courts. Our theoretical model builds on Miceli and Coşgel (1994), who construct a model of judge decision-making under reversal aversion. Reversal aversion of judges at lower federal courts is well documented in the empirical literature(cf. Songer et al., 1994; Randazzo, 2008; Boyd, 2015b). Additionally, Zorn and Bowie (2010) and Cohen and Yang (2019) emphasize that the importance of judge ideology for rulings decreases with judge disrection. This lends further support to our identification approach, as district courts are more strongly monitored than courts of appeals and the Supreme Court is not monitored at all.[3]

4.3 The Effect of Supreme Court Ideology on District Court Rulings

Analyzing district court rulings across U.S. states, we establish that a conservative ideological shift of the Supreme Court induces an increase in the share of pro-business rulings in states with liberal district courts relative to states with conservative district courts.

[3] Choi et al. (2012) argue that the Supreme Court only weakly affects courts of appeals, stating the low rate at which decisions of courts of appeals are reversed at the Supreme Court. However, what they interpret as a low risk of reversal on the side of appellate judges might simply be a sign of compliance. If appellate judges are reversal-averse, they can be expected to issue decisions in a way that reduces the risk of reversals, such that reversals will be rare in equilibrium. In this case, the threat of reversal is still an important determinant of the decisions of appellate judges. Our empirical results clearly indicate that ideological leanings of Supreme Court justices affect district court rulings – arguably passing through the courts of appeals – in a way that is consistent with reversal aversion of both district and appellate judges.

4.3.1 Theory

To fix ideas, we present a simple model which guides our identification of the effects of Supreme Court ideology on district court rulings. We build upon the model of judge decision-making developed by Miceli and Coşgel (1994). In this model, we focus on a specific factor that potentially determines case outcomes: judge ideology. While existing laws and precedent are undoubtedly the most important predictors of case outcomes, there is a large literature that exposes substantial effects of additional, even potentially unrelated factors, see Section 4.2.

Judges have two sources of utility from a particular ruling $r \in [-1, 1]$, where $r = 1$ represents the most conservative and $r = -1$ the most liberal ruling. The first source of utility originates from private preferences over the case at hand, $V(r)$. This source of utility reflects what we summarize as ideological leanings and includes, for example, the political views and the theory of the law of the judge. This utility component is larger, the closer the actual decision r resembles the private preferences. The second source of utility originates from the judge's reputation. Reputational utility is given by $R(r)$ and is meant to capture increased promotion chances of the judge due to a better reputation. While Miceli and Coşgel (1994) focus on future citations, our focus is on the probability of a decisions being reversed by higher courts, i.e., by the circuit courts or in the last instance by the Supreme Court.[4] See Section 4.2 for an overview of the literature on reversal aversion.

We consider the representative (average) district court judge in state s, called judge s. The overall utility of judge s at time t is given by

$$U_s(r_{s,t}) = V_s(r_{s,t}) + R(r_{s,t}).$$

The private utility of judge s is

$$V_s(r_{s,t}) = -\frac{\kappa}{4} \cdot (r_{s,t} - dci_s)^2,$$

where dci_s (for district court ideology) summarizes the ideological leaning and $\kappa > 0$ determines the preference weight on ideology.[5] The reputational utility of judge s is

$$R(r_{s,t}) = -q(r_{s,t}, sci_t),$$

where q is the probability of reversal and sci_t is the ideology of the Supreme Court.

[4] For simplicity, the model only includes district court judges and the Supreme Court. However, the results from a nested model version including circuit courts are qualitatively the same. The circuit courts can be thought of as passing through the guidelines set by the Supreme Court to the district courts – potentially imperfectly so because appellate judges may be able to incorporate their own ideological orientation.

[5] In the econometric analysis we use an interaction term between time-variant Supreme Court ideology and time-invariant district court ideology as our main regressor. Therefore, the time index on district court ideology is dropped. See Section 4.3.2 for a detailed discussion.

As previously stated, a large literature (cf. Boyd, 2015a; Benesh and Reddick, 2002; Cannon and Johnson, 1984; Wasby, 1970; Songer et al., 1994) establishes that while judges at lower courts tend to follow Supreme Court guidance when the Supreme Court's orientation is unambiguous, they also use the leeway an ideologically rather neutral Supreme Court allows in order to rule in accordance with their own ideological preferences. To keep things simple, we carry these findings to extremes (without changing the qualitative results) and postulate

$$q\left(r_{s,t}, sci_t\right) = sci_t^2 \cdot \left(r_{s,t} - sci_t\right)^2 / 4.$$

This implies that a neutral Supreme Court ($sci = 0$) overturns neither clearly liberal nor clearly conservative decisions and that an ideologically clear Supreme Court ($sci = -1$ or $sci = 1$) overturns every decision that is fully at odds with its own ideology.

Under this assumption for the behavior of the Supreme Court, the optimal behavior of a district court judge can be expressed as the following maximization problem

$$\max_{r_{s,t}} -\kappa/4 \cdot \left(r_{s,t} - dci_s\right)^2 - sci_t^2 \cdot \left(r_{s,t} - sci_t\right)^2 / 4.$$

Maximization with respect to the ruling $r_{s,t}$ results in the first order condition

$$-2\kappa/4\left(r_{s,t} - dci_s\right) - 2 \cdot sci_t^2 \cdot \left(r_{s,t} - sci_t\right)/4 = 0,$$

which can be solved for the optimal decision

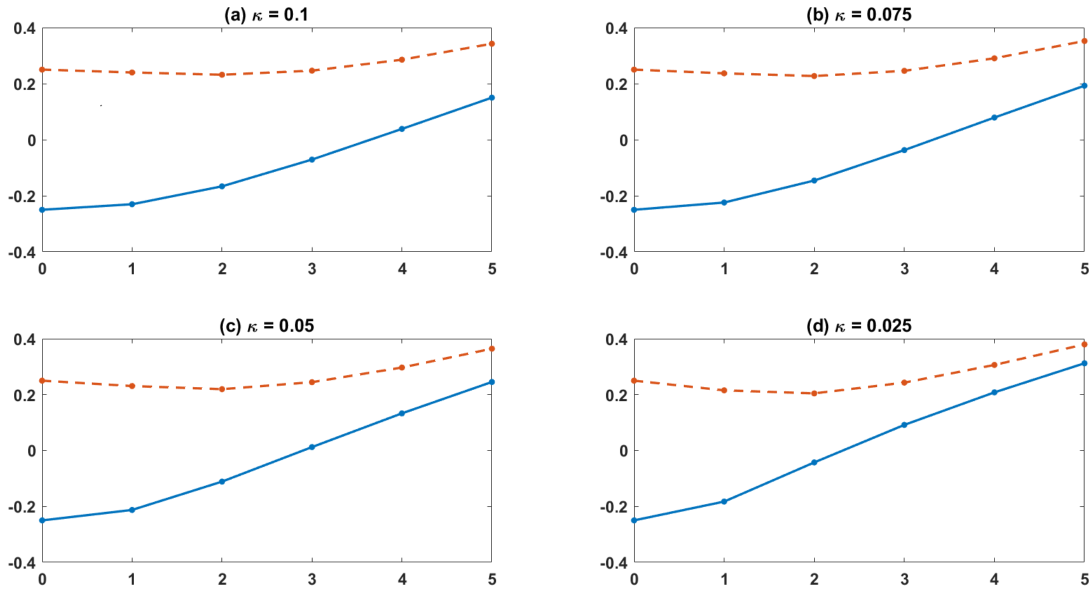
$$r_{s,t}^* = \frac{\kappa}{\kappa + sci_t^2} \cdot dci_s + \frac{sci_t^2}{\kappa + sci_t^2} \cdot sci_t.$$

It follows that the optimal ruling of a district court judge is a weighted average of the judge's own ideology dci_s and Supreme Court ideology sci_t. The respective weights depend on the preference parameter κ and on the unambiguity of the ideological orientation of the Supreme Court. Specifically, when the Supreme Court is rather balanced ideologically (i.e., sci_t takes values close to zero), the weight on dci_s is close to one and rulings are mainly based on district court judges' own preferences. By contrast, when the Supreme Court has a clear ideological leaning (i.e., sci takes values close to -1 or close to 1), rulings mainly depend on Supreme Court guidance.

Next, assume that the ideological leaning of the Supreme Court changes by $\Delta sci = sci_{t+\tau} - sci_t$. Taking the ideology dci_s of a district court judge as given, the change in the optimal decision of judge s caused by this change in Supreme Court ideology, $\Delta r_s = r_{s,t+\tau} - r_{s,t}$, can be calculated as

$$\Delta r_s = \kappa \cdot \left(\frac{1}{\kappa + sci_{t+\tau}^2} - \frac{1}{\kappa + sci_t^2}\right) \cdot dci_s + \left(\frac{sci_{t+\tau}^2}{\kappa + sci_{t+\tau}^2} \cdot sci_{t+\tau} - \frac{sci_t^2}{\kappa + sci_t^2} \cdot sci_t\right). \quad (4.1)$$

Figure 4.3. Model-Predicted District Court Rulings



Note: These graphs depict the simulated rulings in two different district courts: a court with a liberal district court judge A ($dci_A = -0.25$) and a court with a conservative district court judge B ($dci_B = 0.25$). Supreme Court ideology increases linearly from $sci_0 = 0$ to $sci_5 = 0.4$.

Suppose that Supreme Court ideology is positive and increases, i.e., $sci_{t+\tau} > sci_t > 0$ as in our empirical sample, see Figure 4.1. Then, as Equation (4.1) illustrates, this change in Supreme Court ideology induces an increase in the conservatism of district court rulings that is more pronounced the more liberal the considered district court judge (i.e., the lower dci_s) is.

Figure 4.3 illustrates this point in an example where Supreme Court ideology increases linearly from zero to 0.4 (a stylized description of the empirical development illustrated in Figure 4.1). We compare the rulings of a rather liberal district court judge A with $dci_A = -0.25$ with the rulings of a rather conservative judge B with $dci_B = 0.25$ (in our empirical sample this is roughly a comparison of New York and Wyoming). Accounting for the large reversal aversion documented in the literature, see Section 4.2, we use four relatively small values of the preference parameter κ. While rulings turn more conservative in both courts, the increase in conservatism of the Supreme Court induces rulings of the liberal district court judge A to become substantially more conservative relative to rulings of the conservative district court judge B.

In our econometric analysis, we make use of this differential impact of Supreme Court ideology across district courts. We estimate a regression with average district court rulings (where s now represents a state instead of a judge) $r_{s,t}$ as the dependent variable, year fixed effects η_t, state fixed effects δ_s, and the interaction between Supreme Court ideology and district court ideology, $sci_t \cdot dci_s$, (and control variables $X_{s,t}$) as independent variables

$$r_{s,t} = \gamma \cdot sci_t \cdot dci_s + \beta \cdot X_{s,t} + \delta_s + \eta_t + \varepsilon_{s,t}. \tag{4.2}$$

Table 4.1. Illustration of the Econometric Procedure

(a) Average Rulings for Two States and Two Years

Year	State	sci	dci	r			
				$\kappa = 0.1$	$\kappa = 0.075$	$\kappa = 0.05$	$\kappa = 0.025$
0	A	0	-0.25	-0.25	-0.25	-0.25	-0.25
5	A	0.4	-0.25	0.15	0.1926	0.2452	0.3122
0	B	0	0.25	0.25	0.25	0.25	0.25
5	B	0.4	0.25	0.3423	0.3521	0.3643	0.3797

(b) Calculation of the Interaction Effect

	$\kappa = 0.1$	$\kappa = 0.075$	$\kappa = 0.05$	$\kappa = 0.025$
$\Delta r_A = r_{A,5} - r_{A,0}$	0.4	0.4426	0.4952	0.5622
$\Delta r_B = r_{B,5} - r_{B,0}$	0.0923	0.1021	0.1143	0.1297
$\Delta\Delta r = \Delta r_A - \Delta r_B$	0.3077	0.3404	0.3810	0.4324
$\Delta sci = sci_5 - sci_0$	0.4	0.4	0.4	0.4
$\Delta dci = dci_A - dci_B$	-0.5	-0.5	-0.5	-0.5
$\widehat{\gamma} = \Delta\Delta r/(\Delta sci \cdot \Delta dci)$	-1.5385	-1.7021	-1.9048	-2.1622

To understand the role of the interaction effect in Equation (4.2), suppose we observe two states, A and B, in two years, t and $t+\tau$. In such a setting, the estimated coefficient on the interaction term $\widehat{\gamma}$ is given by

$$\widehat{\gamma} = \frac{\Delta\Delta r}{\Delta sci \Delta dci} = \frac{r_{A,t+\tau} - r_{A,t+\tau} - (r_{B,t+\tau} - r_{B,t})}{(sci_{t+\tau} - sci_t) \cdot (dci_A - dci_B)}, \tag{4.3}$$

where $\Delta\Delta r$ is the difference between the change in average rulings in the two states, Δsci is the change in Supreme Court ideology, and Δdci is the difference in ideological leanings of the two states' district courts.

In our model, $\Delta\Delta r$ is given by

$$\Delta\Delta r = \kappa \cdot \left(\frac{1}{\kappa + sci_{t+\tau}^2} - \frac{1}{\kappa + sci_t^2} \right) \cdot \Delta dci. \tag{4.4}$$

Hence, Equation (4.3) evaluates as

$$\widehat{\gamma} = -\left(\frac{\kappa}{\kappa + sci_{t+\tau}^2} + \frac{\kappa}{\kappa + sci_t^2} \right) \frac{1}{(sci_{t+\tau} - sci_t)}, \tag{4.5}$$

which is derived by substituting Equation (4.4) into Equation (4.3) and rearranging terms. Consequently, when the Supreme Court is rather conservative, the model predicts the coefficient on the interaction term to be negative.

Table 4.1 illustrates this estimation approach using the example from Figure 4.3. In particular, the upper part of the table shows the average rulings in the two states in years 0 and 5 of the example in panel form. Rulings in both states become more conservative, but the increase in conservatism is more pronounced in the state with the liberal district court judges, $\Delta r_A > \Delta r_B > 0$, $\Delta\Delta r > 0$. This implies that the interaction term is assigned a negative coefficient, $\widehat{\gamma} = \Delta\Delta r/(\Delta sci \cdot \Delta dci) < 0$. Quantitatively, for the considered values of the preference weight κ, resulting coefficients lie between -1.5 and -2.2.[6]

4.3.2 Evidence

In this Section, we empirically assess the model prediction that increasing conservatism of the Supreme Court renders district court rulings relatively more conservative in states with rather liberal district court judges by estimating Regression (4.2). In Section 4.4, we will use the thus identified ideological variation in state-specific court rulings (caused by changes at the Supreme Court and thus arguably exogenous to state-specific developments) as independent variable in regressions seeking to explain labor market outcomes. This makes the state the relevant level of our analysis, as detailed labor market data from the Current Population Survey is not available on a less aggregate level.

Variables, Data Sources, and Sample Selection

In the following, we describe our sample, give an overview of the variables used in our regressions, and state the sources from which these variables are obtained.

District Court Rulings For district court rulings $r_{s,t}$, we use the Carp-Manning U.S. District Court Database compiled by Carp and Manning (2016). All cases in this dataset are taken from the Federal Supplement, which is the primary source of published U.S. district court decisions. In practice, even though the publisher has no legal monopoly over the court opinions, any decision that a sitting federal district judge submits has been published in the Federal Supplement. Decisions to publish are mainly determined by the official publication guidelines and not by the judges' ideological tendencies (cf. Swenson, 2004).[7] These official guidelines generally encourage publication if the opinion lays down a new rule of law, alters an existing rule, criticizes an existing rule, or changes the way in which an existing rule has been applied

[6] Note from Equation (4.5) that the difference between the district court ideologies in the two states is irrelevant for the value of the estimated coefficient $\widehat{\gamma}$, as $\Delta\Delta r$ is proportional to Δdci (see Equation (4.4)). Hence, although the two district court ideologies are chosen arbitrarily for an illustrative example, the values for $\widehat{\gamma}$ in Table 4.1 are informative about what to expect for a sample where the ideology of the Supreme Court develops in a way as displayed in Figure 4.1.

[7] About 20% of all cases decided in district courts are eventually published in the Federal Supplement.

(cf. West Publishing Company, 1994). Hence, rulings in our dataset are rulings on cases with a high precedential value and are thus bound to be influential for a large number of other (unpublished) cases.

The database contains a total of 23,135 rulings of district courts in the 50 states from 1978 to 2011 that can be clearly labeled as either conservative (+1) or liberal (-1) and that can be categorized as Economic Regulation and/or Labor Cases. The majority of cases falling into this category are employee versus employer cases, which make up over one third of all included rulings. Cases of company versus either a union or the NLRB make up close to 15%. In general, pro-business decisions are considered to be conservative rulings. In a dispute between workers and their employer decisions in favor of the workers are regarded as liberal, whereas decisions in favor of the employer are regarded as conservative. In regulation cases, decisions for the government are considered to be liberal. Our dependent variable $r_{s,t}$ is the average ideological leaning of rulings in state s and year t. This variable would take the value 1 (-1) if all cases were decided in a conservative (liberal) way.

Supreme Court Ideology For the ideology of Supreme Court justices sci_t, we use the ideal point estimates calculated by Bailey (2013). The ideology scores from Bailey (2013) are chosen over the more common Martin-Quinn scores, since the former are able to distinguish between shifts in ideologies and shifts in case composition by using bridging information such as positions of justices on previous cases. With changing ideological leanings of Supreme Court justices, the case composition is bound to change as well.[8] If ideological leanings and case composition change simultaneously, the effect on liberal voting percentages of Supreme Court justices, on which the Martin-Quinn scores are based, is unclear. The use of briding information allows Bailey (2013) to disentangle the two effects.[9] In the regressions, we define sci_t as the median Bailey score of Supreme Court justices.

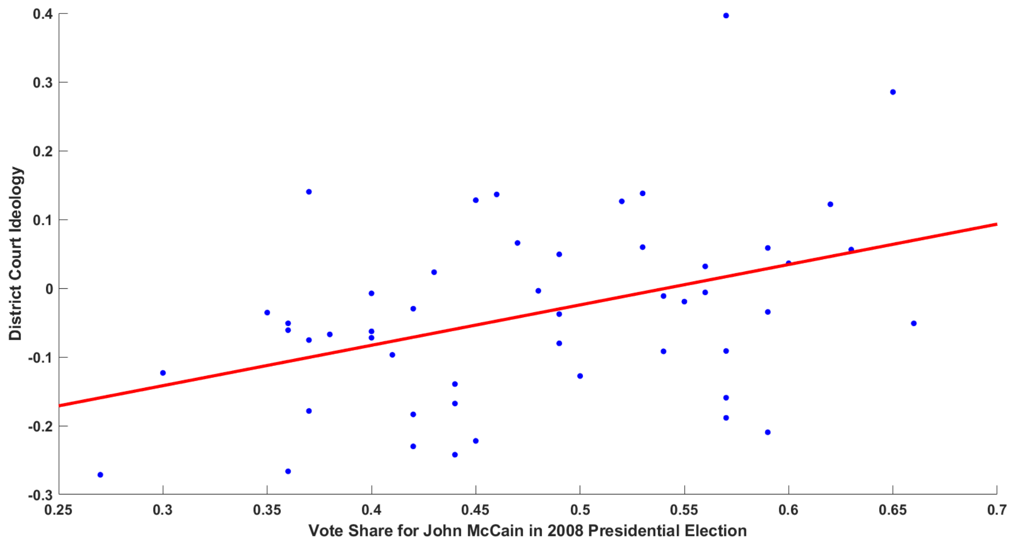
District Court Ideology For the ideology of district court judges dci_s, we use information on ideologies provided by Boyd (2015a).[10] The lack of data on district court judges does not allow for the use of the methodology developed in Bailey (2013) here. As the rulings of district court judges will arguably be influenced by Supreme Court ideology, we refrain from using ideology scores that are based on rulings and use scores that are calculated based on the

[8] Cases are heard by the Supreme Court if they are supported by at least four Supreme Court justices. Thus, with more conservative justices, one would expect some cases to be chosen that would not be heard by a more liberal Supreme Court. This pertains, for example, to cases with liberal rulings of the lower courts, that a liberal Supreme Court would be very unlikely to overturn.

[9] The Bailey scores are bounded between -2 and 2, with a clearly liberal and a clearly conservative justice fixed at -1.5 and 1.5 for reference. In the data, median Baily score of the Supreme Court between 1950 and 2011 has never been below -1.1 and has never exceeded a value of 0.6. Thus, a value of -1 already constitutes an exceedingly liberal Supreme Court that can be expected to overturn overly conservative rulings at lower courts. The reverse argument holds for the value 1.

[10] The calculation of the ideology scores from Boyd (2015a) follows the methodology developed in Giles et al. (2001) and extended in Epstein et al. (2007). Ideology scores are bounded between -1 and 1.

Figure 4.4. District Court Ideology and 2008 Voting Shares for John McCain



Note: This graphs plots the average Boyd ideology score of district court judges by state for the time period between 1936 and 1977 against the voting share for John McCain in the 2008 presidential election, obtained from the Federal Election Commission.

appointment process for federal judges instead. The Boyd scores exploit the norm of senatorial courtesy: if a judge is appointed from a state where the president and a senator (both senators) share a political party, the judge is assigned the ideology score of the senator (the average of the senators), else the judge is assigned the ideology score of the president. We link the Boyd data to information on confirmation, reassignment, and retirement dates of district court judges from the Biographical Directory of Article III Federal Judges provided by the Federal Judicial Center.

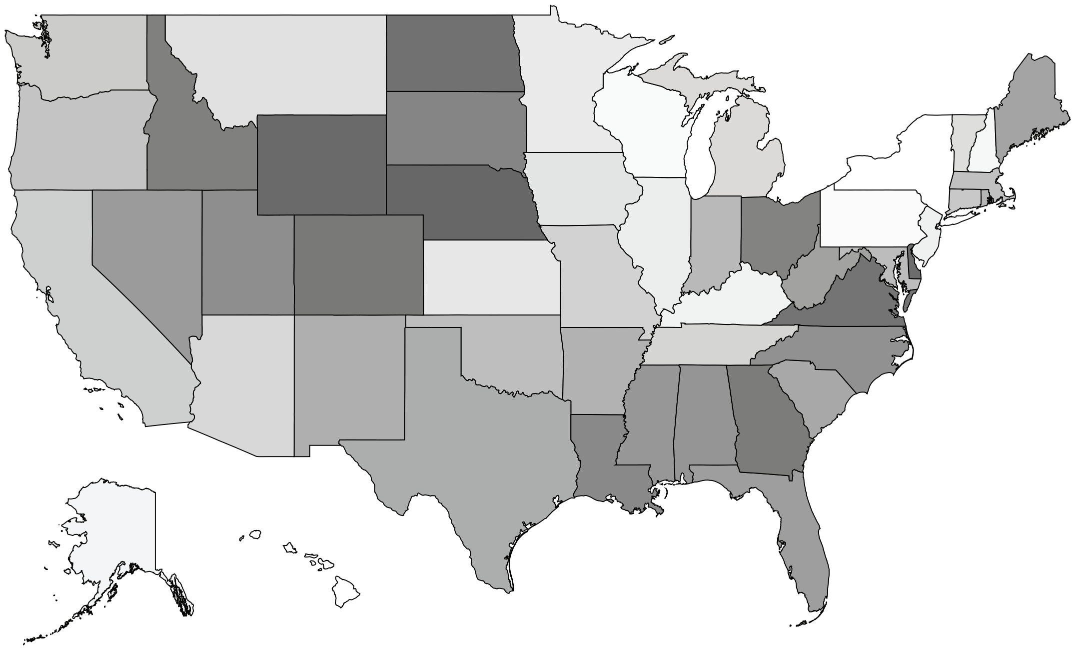
While the ideology of judges at a district court is a constant in our model, in reality it can change over time due to changes in judge preferences, the confirmation of new judges, and the retirement of old ones. In order to avoid endogeneity in the ideology measure for district courts, we use the average Boyd ideology score of district court judges in state s that have been serving between 1936 (the first year for which there are ideology scores available from the Boyd dataset) and 1977 (the year before our regression sample begins). Formally, we define

$$dci_s = \frac{1}{\sum_{j \in J_s} y_j} \sum_{j \in J_s} y_j B_j,$$

where dci_s is the average ideology score for state s, J_s is the set of district judges serving in state s between 1936 and 1977, y_j is the term length for judge j in this time frame, and B_j is judge j's ideology score.

This pre-sample ideology measure is informative about the ideological leanings of a state's district courts judges in the regression period, as ideological leaning of judges display substantial persistence. Federal judges are appointed for life and hence serve (on average) long terms until

Figure 4.5. Average Ideology Score of District Court Judges by State, 1936–1977



Note: This graphs depicts the average Boyd ideology score of district court judges by state for the time period between 1936 and 1977. Darker colors indicate conservatism and lighter colors indicate liberalism.

they retire voluntarily. Reappointments to other courts are rare. Further, strategic retirement plays an important role at district courts, perpetuating ideological leanings beyond the current judges' retirements. Specifically, district court judges tend to retire when the current President is ideologically similar to themselves. As an extreme case, the district court for the district of North Dakota has never had a judge who was appointed by a Democratic president since 1954. In the Boyd database, the average ideology of judges at a district court is highly autocorrelated, with most district courts displaying a yearly autocorrelation of about 0.8 and some an autocorrelation of over 0.95.[11] Thus, while the pre-sample ideology measure we use is indeed informative about judge ideology within our regression sample, it is unrelated to potentially endogenous ideological changes occurring within our sample.

In most cases, a state's district court ideology coincides with the perceived political ideology in that state, see Figure 4.4. However, there are a few exceptions like Kentucky (which has rather liberal district courts) or Delaware (which has a rather conservative district court). The correlation between the 2008 general-election voting for John McCain from the Federal Election Commission (as an indicator for a states general conservatism) and our district court ideology measure is 0.4. For our analysis, it is advantageous that this correlation is not too high, such that we can actually disentangle a state's district court ideology from the general political leaning of the state. A map depicting the liberalism/conservatism of states according to their district courts is provided in Figure 4.5. The map shows some concentration of rather liberal district courts in the northeast, with New York, Pennsylvania, and New Hampshire belonging

[11]The evolution of the average ideology score by district court is shown in C.1

to the five states with the most liberal district court judges according to our measure. We have tested for regional variation in treatment effects, which would indicate a need to cluster standard errors despite the fact that we include state fixed effects in the regressions (cf. Abadie et al., 2017), but could not find any systematic pattern.

Control Variables We control for variables that can be expected to affect court rulings beyond the interplay between Supreme Court ideology and district court ideology. We account for the case composition, using information from the Carp-Manning database, and for judge composition along characteristics such as age, race, gender, and experience (which have been identified as determinants of rulings by the literature, see Section 4.2), using information from the Biographical Directory of Article III Federal Judges and the Carp-Manning database. We take the role of circuit courts into account by controlling for the average Boyd score of the responsible appellate judges. To ensure that our results are not driven by compositional changes at the district courts, we include the share of district court judges appointed by a Republican president.[12] To capture non-judicial ideological forces potentially affecting district court rulings, we also control for well-known determinants of ideological leanings of the state's population, such as population size, urban density, age, and racial composition, from the Current Population Survey (CPS). Further determinants, like the political party of the governor and the majority parties in the state's legislative chambers, are obtained from the State Partisan Composition collected by the National Conference of State Legislatures and additionally included as controls.

Finally, since the autocorrelation of the average judge ideology score at a district court is below one, average rulings by district courts might show some tendency to converge towards the middle, i.e., rulings at initially rather liberal district courts might tend to become more conservative over time independent of developments at the Supreme Court. To pick up such mean-reverting tendencies, we also include the lagged dependent variable in the set of control variables.

The literature, see Section 4.2, has also documented that court rulings can be affected by economic conditions. In our preferred specification we leave out economic indicators as control variables for two reasons. First, there is no obvious correlation between changes in state-specific economic outcomes and changes in Supreme court ideology, such that the omission of economic variables is unlikely to bias the coefficient on the interaction between Supreme Court ideology and our constant measure of district court ideology. Second, we argue that economic outcomes are themselves affected by court rulings, such that including economic variables as controls would erroneously take out the correlation between economic outcomes and court rulings that is driven by causal effects *from* court rulings *to* economic outcomes. To corroborate our findings, we consider additional specifications where we include state-specific labor market outcomes and state GDP growth as controls in C.3.

[12] A detailed description of the evolution of this share by district court is provided in C.2

Sample Selection Our sample runs from 1978 to 2011. We choose 1978 as the starting date because of two reasons. First, our measure of Supreme Court ideology reaches a value of zero in 1978 and stays above this value for the entire sample period. Thus, liberal district courts will be unambigously more affected by the shifts in Supreme Court Ideology over our entire sample period. Second, state-level labor market data is only available from the late 1970s onwards in the CPS. The end date is chosen because ideology scores for the Supreme Court by Bailey (2013) are only available until 2011. We concentrate on the 50 states and exclude the District of Columbia because many cases heard at the district court for D.C. do not specifically relate to the D.C. labor market but concern the federal government.

In principle, our sample contains 34 years $\times$ 50 states = 1700 state-year observations. However, there are 79 state-year combinations with no rulings falling into the Economic Regulation and/or Labor Cases category. Since we also use lagged rulings as a control variable in our regressions, we lose another 62 observations due to years without rulings in certain states.[13] Missing values for other control variables induce the loss of another 60 observations.[14] This leaves us with a consistent sample of 1499 state-year observations for which we observe all our variables.

Descriptive Developments

We begin our analysis by looking descriptively at the evolution of the share of conservative rulings in the district courts. For convenience, Figure 4.2, which is a clear first indication that, as predicted by our model, the share of conservative rulings has increased in states with liberal district courts relative to states with conservative district courts between 1978 and 2011, is repeated here.

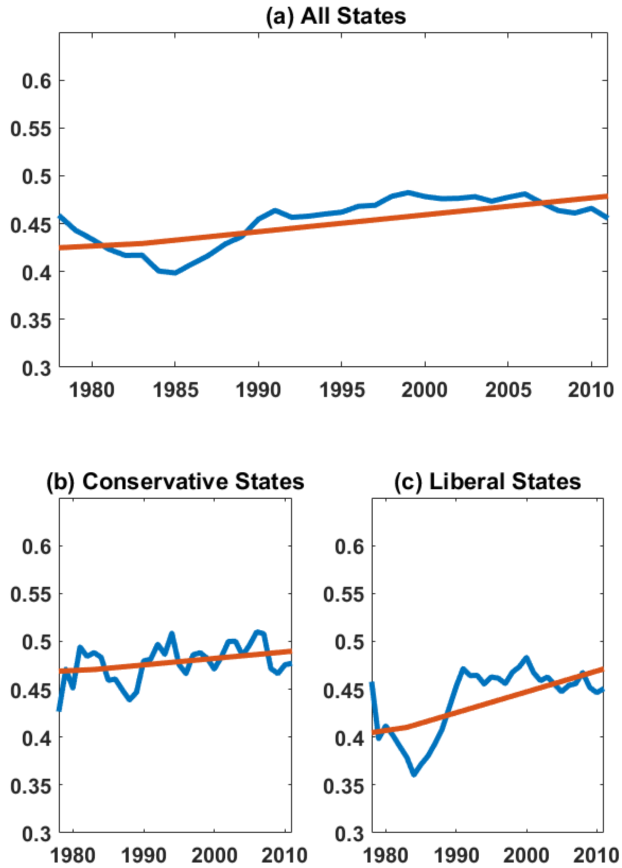
Figure 4.7 compares the evolution of the ideological leanings of Supreme Court justices to the evolution of the ideological leanings of district court judges.[15] As both Supreme Court justices and district court judges are appointed by the president, the two series naturally display a high positive correlation. Still, the ideology scores depicted in Figure 4.7 suggest that the conservative shift of district court judges is much more modest over the entire sample period. This ameliorates potential concerns that the relative increase in conservative rulings in liberal

[13]The Carp-Manning U.S. District Court Database does not include rulings in the economic category for Alaska in 1980, 1987, 1990, 1991, 1997, 2001, 2004, and 2009, for Arizona in 1981, for Arkansas in 2000, for Delaware in 2011, for Hawaii in 1985, for Idaho in 1977, 1979, 1991, 1994, 1997, 1999, 2000, and 2006, for Iowa in 1978, for Kentucky in 1980 and 2000, for Maine in 1977, 1978 and 1981, for Montana in 1984, 1990, 1991 and 1993, for Nebraska in 1983, 1988, 1991, 2006 and 2007, for Nevada in 1994, 2007, and 2008, for New Hampshire in 1979, 2001, 2003, and 2011, for New Mexico in 1979, 1981, 1982, 1988, 1998, and 2006, for North Dakota in 1977, 1979, 1988, 1990, 1992, 1993, 1994, 1997, 1998, 1999, and 2001, for Rhode Island in 1981, for South Dakota in 1987, 1988, 1991, 1998, and 1999, for Utah in 1978, for Vermont in 1981, 1982, 1984, 1986, 1988, 2010, and 2011, for Washington State in 1978 and 1979, and for Wyoming in 1977, 1981, 1984, 1998, 2003, 2006, 2007, and 2011.

[14]Our urban-density variables are not reported in the CPS before 1986 for Delaware, Idaho, Maine, Montana, Nevada, New Hampshire, North Dakota, and South Dakota, as well as between 1986 and 1995 for Wyoming.

[15]Keep in mind that the ideology scores of district court judges are based on their appointment process and are thus unaffected by changes in rulings or case composition.

Figure 4.6. Share of Conservative District Court Rulings in Economic and/or Labor Cases



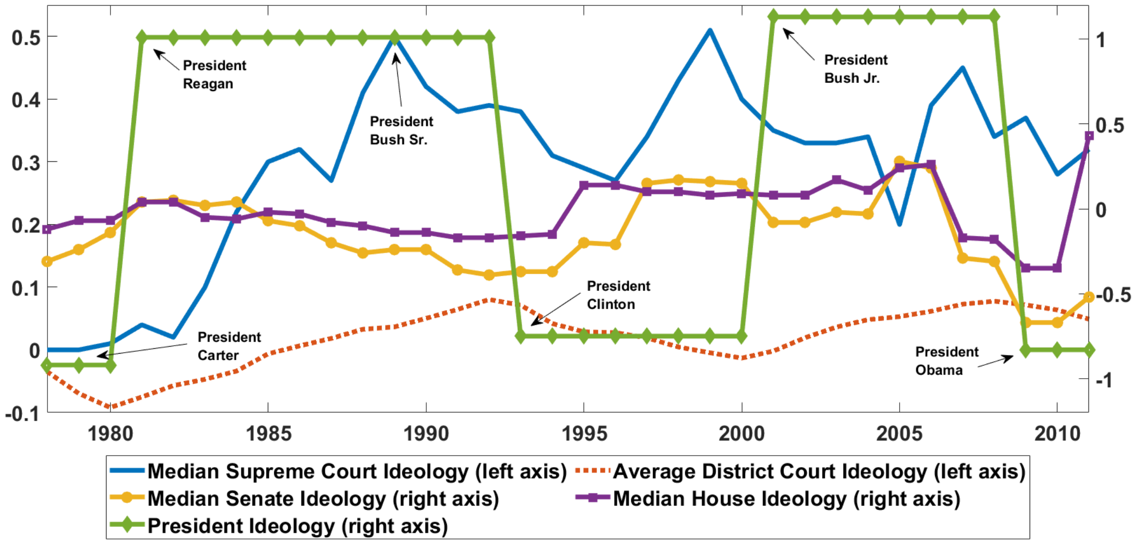
Note: This graphs depicts the five-year moving average of the share of conservative rulings for cases in the Economic and/or Labor Cases category in the Carp-Manning U.S. District Court Database compiled by Carp and Manning (2016) for all states, for states with conservative district courts ($dci_s > 0$), and for states with liberal district courts ($dci_s < 0$). The orange lines are linear trends.

states might not be driven by ideologically unchanged district court judges following the increasingly conservative guidelines set by the Supreme Court but by a concomitant shift of district court ideology towards the conservative end of the ideological spectrum. To further address this concern, we include the share of district court judges appointed by a Republican president as a control variable in our regressions as explained above. Median ideology scores for the Senate and the House of Representatives experience only very modest changes over our sample period (which will arguably be completely captured by our time fixed effects).

Figure 4.8 plots the average ideology score of district court judges by state and year against last year's value. Most observations concentrate around the 45-degree line, indicating a high persistence in district court ideology by state. This persistence is key to our identification, which relies on long-run ideological differences between persistently rather liberal courts and persistently rather conservative courts.

A simple regression of the average ideology score of district court judges by state and year on its own lag and state fixed effects gives a coefficient on the lag of 0.92. Thus, while district

Figure 4.7. Ideological Leanings of Supreme Court Justices, District Court Judges, the President, the Senate, and the House of Representatives

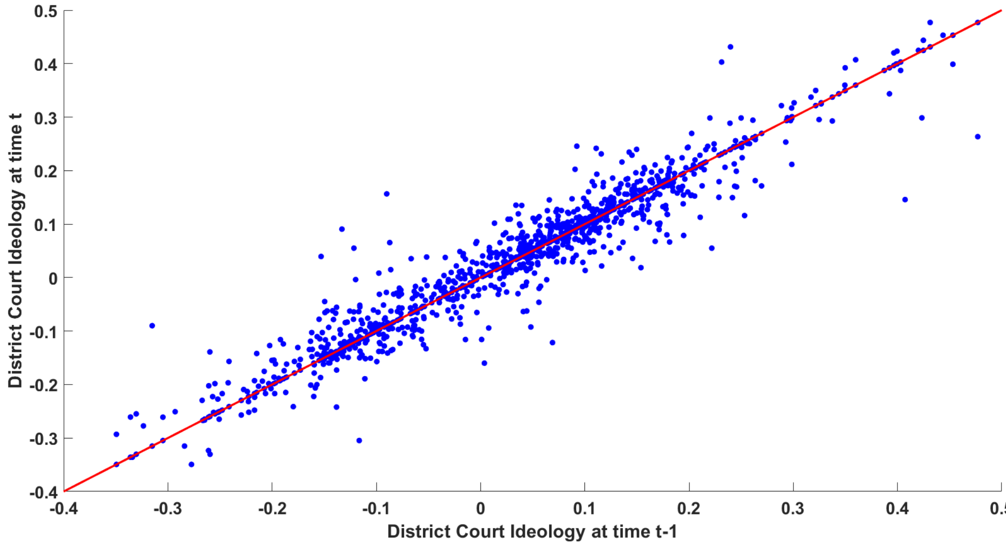


Note: This graph depicts the ideal point estimates provided in the dataset to Bailey (2013) for the ideological leanings of the median Supreme Court justice, the median senator on the U.S. Senate, the median representative in the House of Representatives, and the president between 1978 and 2011, as well as the average Boyd ideology scores for district court judges between 1978 and 2011. Again, positive values are tantamount to conservative ideological leanings, while negative values imply liberal ideological leanings.

court ideology is highly persistent, it displays some tendency to revert to the middle of the ideological spectrum over time, reflecting that some rather liberal (conservative) judges retire during the presidency of a Republican (Democratic) president in each year. One may argue that this induces rulings in initially rather liberal district courts to become more conservative over time, independent of ideological developments at the Supreme Court. For this reason, we include the lagged dependent variable as a control in our regressions to capture mean-reverting tendencies in rulings by state, as described above. Additionally, we also directly control for the share of judges appointed by a Republican president in our regressions.

While the descriptive evidence indicates a high persistence of district court ideology over time, it is silent on the underlying reason for initial ideological differences. We argue that these differences are likely driven by historical events that took place before the start of our sample period. To substantiate this argument we take a closer look at two striking cases in our sample: the unexpectedly liberal district courts of Kentucky and the surprisingly conservative district court of Delaware. The U.S. District Court of Eastern Kentucky was established in 1901, implying that the first judges at this court were all appointed by President Roosevelt (and President Kennedy in one case). At the U.S. District Court of Western Kentucky, between 1935 and 1954 all new judges (including the judge appointed to the newly established seat in 1936/1937) have been appointed by either President Roosevelt or President Truman. As for the U.S. District Court of Delaware, following the establishment of a new seat and the death of

Figure 4.8. Correlation of Ideology Scores of District Court Judges by State and Year, 1978–2011



Note: This graph plots the average Boyd ideology score by state and year against last year's value. The 45-degree line is indicated in red.

two rather liberal judges, President Eisenhower was able to appoint three rather conservative judges between 1955 and 1958, shaping the court for several decades.

Econometric Results

The regression results for district court rulings are reported in Table 4.2. Column (1) constitutes our preferred specification, featuring the full set of control variables. Column (2) excludes the lagged dependent variable, Column (3) excludes all control variables except the lagged dependent variable, and Column (4) excludes all control variables.

As predicted, the coefficients on the interaction term between Supreme Court ideology and district court ideology are negative in all four specifications. This means that the shift in Supreme Court ideology did indeed induce rulings to become more conservative in states with rather liberal district courts relative to states with rather conservative district courts. Quantitatively, estimates are about -1.8 to -2 and hence fall in the range suggested by our model (see Table 4.1). Column (2) shows a somewhat larger coefficient in absolute value than Column (1), indicating that taking into account the tendency of rulings in a state to converge to the center over time is indeed important. However, as the coefficients are fairly similar, this tendency does not seem to matter too much. Columns (3) and (4), which leave out certain control variables, illustrate that our results do not depend on the specific set of included controls.

We perform several checks in order to assess the robustness of our findings. Specifically, we include controls for local labor market conditions, include higher lags of the dependent variable, weigh observations by the number of rulings per state population, and use a moving average

Table 4.2. Regression Results for District Court Rulings

	(1)	(2)	(3)	(4)
Supreme Court ideology	-1.9673	-2.0102	-1.7978	-1.8778
× district court ideology	(0.7104)	(0.7095)	(0.6904)	(0.6905)
	p=0.0057	*p=0.0047*	*p=0.0093*	*p=0.0066*
Observations	1499	1499	1499	1499
R^2	0.2619	0.2612	0.0918	0.0885
Lagged dependent variable	yes	no	yes	no
State demographics	yes	yes	no	no
Court, judge, and case characteristics	yes	yes	no	no
State gov. and leg. controls	yes	yes	no	no
Year fixed effects	yes	yes	yes	yes
State fixed effects	yes	yes	yes	yes

Note: The standard errors are reported in parentheses. The p-values are reported below the standard errors.

of our measure of Supreme Court ideology sci_t. In all of these specifications the coefficient on the interaction term between Supreme Court ideology and district court ideology remains distinctly negative and highly statistically significant. See C.3 for the detailed results.

4.4 Labor Market Effects of Judicial Ideology

In this section, we exploit that the interaction term $sci_t \cdot dci_s$ induces an increase in the share of pro-business rulings in states with liberal district courts relative to states with conservative district courts to estimate the effect that ideological tendencies in court rulings exert on the labor market. After presenting the empirical results, we rationalize them in a simple search and matching model with wrongful termination lawsuits.

4.4.1 Evidence

In order to identify the economic effects of jurisdiction on the labor market, we now use $sci_t \cdot dci_s$ in regressions with labor market outcomes as the dependent variable. Specifically, we estimate

$$z_{s,t} = \gamma^z \cdot sci_t \cdot dci_s + \beta^z \cdot \tilde{X}_{s,t} + \delta_s^z + \eta_t^z + \varepsilon_{s,t}^z. \tag{4.6}$$

where $z_{s,t}$ is a specific labor market outcome of interest in state s and year t. $\tilde{X}_{s,t}$ is the set of time-varying state-specific variables that can be expected to affect labor market outcomes directly. State and time fixed effects are captured by δ_s^z and η_t^z. $\varepsilon_{s,t}^z$ is the residual.

Variables and Data Sources

The interaction term $sci_t \cdot dci_s$ remains the regressor of interest.[16] Using this interaction term instead of a direct measure of court rulings in a state isolates the change in state-specific court rulings which is driven by a nation-wide development, i.e., the changing Supreme Court ideology. This strongly ameliorates any concerns about reverse causality. Judge decisions have been shown to be affected by economic conditions (cf. Ichino et al., 2003; Marinescu, 2011), but our interaction term is arguably unaffected by changing labor-market conditions in the specific state. Since the measure of district court ideology is time-invariant and determined from pre-sample data, it does by construction not react to changes in the state's economy. Furthermore, economic conditions may also affect the ideology of the Supreme Court. For example, the Great Recession with its high levels of unemployment is believed to have contributed to the election of Barack Obama in the 2008 presidential elections and thus also to the appointments of the rather liberal justices Sonia Sotomayor and Elena Kagan. Nevertheless, it is likely national economic conditions which affect the Supreme Court and, for our results to be affected by reverse causality, Supreme Court ideology would have to be affected by changes in (the distribution of) state-level labor market conditions.

Empirical methods such as ours have recently been criticized for causing biases, as they might be correlated to previous shocks (cf. Jaeger et al., 2018; Goldsmith-Pinkham et al., 2018). For such a correlation between the interaction term and responses to past shocks to drive our results, one would have to argue that unfavorable past shocks to a state's economy have led to the appointment of more liberal district court judges and are still driving economic performance in our sample, such that the recovery from those shocks drives the positive correlation between the increase in Supreme Court ideology and economic performance in states with rather liberal district court judges. We are confident that the long time period we can use for the calculation of the pre-sample measure of district court ideology makes this a minor issue for our analysis. The average judge (weighted by years in office) who influences our pre-sample measure of district court ideology was appointed in 1956, more than 20 years before the start of our regression sample. Business cycle shocks are usually considered to fade a lot quicker and permanent shocks to a state's economy are taken into account by using state fixed effects.

[16]See Section 4.3 for definitions and sources of sci_t and dci_s.

Labor Market Outcomes For labor market outcomes, which are the dependent variables of our regressions, we draw on the Current Population Survey (CPS). The CPS is a monthly survey of about 60,000 U.S. households conducted by the United States Census Bureau. The sample is representative of the civilian noninstitutional population. We construct yearly data on state-specific unemployment rates, job-finding rates, employment rates, hourly wage rates, other job attributes, employment shares by industry and occupational group, and inequality measures using weights from the Integrated Public Use Microdata Series (IPUMS). More information on the dependent variables can be found in C.5. Due to the small sample size of the CPS in some smaller states, variables for these states are measured rather noisily. We address this issue by weighing observations by state population.

Control Variables We include the following time-varying state-specific variables that can be expected to affect labor market outcomes directly. Note that all variables that are either state-specific but constant or time-varying but determined at the national level are captured by the respective fixed effects. For example, the party holding the Presidency, which is correlated with Supreme Court ideology, see Figure 4.7, does not vary by state and its effects are hence captured by the year fixed effect.

A first set of control variables, taken from the CPS, describes the state's industry and occupational composition. It includes the employment shares in the construction, manufacturing, transportation, trade, financial, and services industries as well as employment share in abstract, routine, and manual occupations, following the categorization by Autor and Dorn (2013).

We further control for a set of state-specific policy measures. This set includes a measure of the tax burden, the state minimum wage, the state's federal intergovernmental revenue and a measure of employment protection laws in the state. The tax burden is the total amount paid in taxes by a state's residents divided by the state's total income computed by the Tax Foundation. Minimum wages are the minimum wage rates by state from Federal Reserve Economic Data. Data on the federal intergovernmental revenue of a state is taken from the State and Local Government Finance Dataset constructed by the Census Bureau through the Annual Survey of State and Local Government Finances. These revenues consist of all monies a state obtains from the federal government. Regarding employment protection, dummies for exceptions from the doctrine of at-will employment are constructed using the data provided in Autor et al. (2006a).[17]

We include controls for state government and legislative majorities. Specifically, we add dummies indicating the party of the governor, the majority party in the state senate, and the majority party in the state house.

In robustness checks, we also include controls for state demographics (like in the regressions for court rulings). To rule out the possibility that our results are driven by some other aggregate

[17] In contrast to other employment protection measures, the empirical literature consistently finds negative employment effects of exceptions from the doctrine of employment at-will, with the only exception being Miles (2000). However, the findings of Miles (2000) have later been disputed by Autor et al. (2004).

Table 4.3. Regression Results for Measures of Labor Market Fluidity

	(1)	(2)	(3)
Dependent variable	Unemployment rate	Job-finding rate	Employment rate
Supreme Court ideology sci_t	0.0705	-0.0565	-0.0831
$\times$ district court ideology dci_s	(0.0208)	(0.0247)	(0.0297)
	p= 0.0007	*p= 0.0223*	*p= 0.0052*
Observations	1499	1499	1499
R^2	0.7561	0.6414	0.8623
Industry and occupation controls	yes	yes	yes
State policy controls	yes	yes	yes
State gov. and leg. controls	yes	yes	yes
Year fixed effects	yes	yes	yes
State fixed effects	yes	yes	yes

Note: The standard errors are reported in parantheses. The p-values are reported below the standard errors.

trend that depends on district court ideology or by some other state-specific trend that depends on Supreme Court ideology, we present specifications in which we control for several additional interaction terms. Furthermore, we control for the possibility that our main regressor, the interaction term between Supreme Court ideology and district court ideology, captures other aggregate or state-specific trends. Finally, to rule out that our results are driven by pre-sample trends, we control for pre-sample income growth. See C.4 for a summary of all of the above-mentioned robustness checks.

Econometric Results

Our main results are summarized in Tables 4.3–4.7. Table 4.3 shows that judicial conservatism tends to promote labor market fluidity.[18] We find that more conservative, i.e. more pro-

[18]Note, the interaction term between sci_t and dci_s measures the effect of rising conservatism in Supreme Court ideology on liberal relative to conservative district courts. Thus, the positive coefficient, e.g. on the unemployment rate, implies that unemployment falls in rather liberal to rather conservative district courts.

Table 4.4. Regression Results for Job Attributes

	(1)	(2)	(3)	(4)
Dependent variable	Avg. hourly wage rate	Vol. PT share	PT/FT wage rate	Union coverage
Supreme Court ideology sci_t	0.1739	0.0375	0.4265	0.1305
$\times$ district court ideology dci_s	(0.0707)	(0.0186)	(0.2065)	(0.0267)
	p= 0.0140	*p= 0.0447*	*p= 0.0391*	*p= 0.0000*
Observations	1499	1499	1499	1499
R^2	0.9933	0.8071	0.4180	0.9666
Industry and occupation controls	yes	yes	yes	yes
State policy controls	yes	yes	yes	yes
State gov. and leg. controls	yes	yes	yes	yes
Year fixed effects	yes	yes	yes	yes
State fixed effects	yes	yes	yes	yes

Note: The standard errors are reported in parantheses. The p-values are reported below the standard errors.

business, rulings increase the employment rate, reduce the unemployment rate, and increase the probability for unemployed people to find a new job. Turning to job attributes (Table 4.4), we find that a larger share of pro-business rulings reduces average hourly wages, the employment share of voluntary part-time workers, and union coverage, while increasing the part-time hourly wage penalty. Hence, as employment increases, labor earnings, workplace flexibility (voluntary part-time employment), and job security (union coverage) all decrease. The rise in the part-time penalty can be seen as an increase in firms' ability to discriminate between different groups of workers in terms of pay, which is brought about by a lower risk of losing lawsuits.

The results concerning occupational employment shares (Table 4.5) and industry composition (Table 4.6) indicate that conservative court rulings also lead to a decline in the routine-manufacturing employment share while increasing the employment share of abstract workers and of employees in the construction and in the service sector.[19] In this sense they accelerate

[19]Obviously, we cannot control for the state's industry-occupation composition in these regressions. For com-

Table 4.5. Regression Results for Occupational Employment Shares

	(1)	(2)	(3)
Dependent variable	Abstract emp. share	Routine emp. share	Manual emp. share
Supreme Court ideology sci_t	-0.0645	0.0633	0.0220
$\times$ district court ideology dci_s	(0.0248)	(0.0250)	(0.0209)
	p= 0.0093	*p= 0.0116*	*p= 0.2932*
Observations	1499	1499	1499
R^2	0.9055	0.8267	0.7951
Industry and occupation controls	no	no	no
State policy controls	yes	yes	yes
State gov. and leg. controls	yes	yes	yes
Year fixed effects	yes	yes	yes
State fixed effects	yes	yes	yes

Note: The standard errors are reported in parantheses. The p-values are reported below the standard errors.

the hollowing out of the middle-class, as workers in routine-manufacturing jobs typically rank in the middle of the income distribution.

Finally, more pro-business rulings also contribute to rising income inequality. Table 4.7 shows results for the 90/10, 90/50, and 50/10 percentile ratios of the distribution of family income.[20] The coefficient on the interaction term is only significant for the 90/10 and 90/50 family income ratios, indicating that the increase in income inequality due to increasingly conservative district court rulings is mainly driven by increasing inequality at the top half of the income distribution.

Intuitively, more pro-business decisions lower costs for firms while also improving their bargaining position. This reduces unemployment at the cost of lower wages and higher inequality. In the subsequent Section 4.4.2 we develop a theoretical model of the labor market

pleteness, Table C.2 in C.4 shows results for further industry groups not included in Table 4.6.

[20] We consider the 80/20, 80/50, and 50/20 income ratios in Table C.3 in C.4 and find similar effects of judicial ideology.

Table 4.6. Regression Results for Industry Employment Shares

	(1)	(2)	(3)
Dependent variable	Construction emp. share	Manufacturing emp. share	Service emp. share
Supreme Court ideology sci_t	-0.0456	0.1428	-0.0930
$\times$ district court ideology dci_s	(0.0160)	(0.0297)	(0.0260)
	p= 0.0044	*p= 0.0000*	*p= 0.0004*
Observations	1499	1499	1499
R^2	0.6692	0.9287	0.9013
Industry and occupation controls	no	no	no
State policy controls	yes	yes	yes
State gov. and leg. controls	yes	yes	yes
Year fixed effects	yes	yes	yes
State fixed effects	yes	yes	yes

Note: The standard errors are reported in parantheses. The p-values are reported below the standard errors.

that makes this argumentation explicit. The empirical results regarding the other considered variables can be understood in a similar way. As the union bargaining power is depressed by higher chances of pro-business rulings, incentives to join a union fall, which further contributes to lower wages and larger income inequality. Furthermore, as the adoption of new technologies proceeds slower in unionized firms due to employment protection (cf. Connolly et al., 1986; Bradley et al., 2017), lower unionization rates might also explain (at least part of) the documented changes in industry employment shares and in the occupational composition.

Quantitative Evaluation of the Results As shift-share results only imply relative effects (in our case the change in states with rather liberal district courts relative to the change in states with more conservative district courts), we construct a thought experiment in order to gauge the quantitative meaning of our results. To translate these relative results into absolute effects, we make the additional assumption that the state with the most conservative district court judges is unaffected by the rightward shift of the Supreme Court. This assumption probably

Table 4.7. Regression Results for Inequality

	(1)	(2)	(3)
Dependent variable	90/10 percentiles	90/50 percentiles	50/10 percentiles
Supreme Court ideology sci_t	-0.3674	-0.1973	-0.1701
$\times$ district court ideology dci_s	(0.1592)	(0.0753)	(0.1331)
	p= 0.0211	*p= 0.0089*	*p= 0.2013*
Observations	1499	1499	1499
R^2	0.8228	0.8281	0.7006
Industry and occupation controls	yes	yes	yes
State policy controls	yes	yes	yes
State gov. and leg. controls	yes	yes	yes
Year fixed effects	yes	yes	yes
State fixed effects	yes	yes	yes

Note: The standard errors are reported in parantheses. The p-values are reported below the standard errors.

understates the effect of shifts at the Supreme Court, as even the most conservative district court will likely experience some effect.

To illustrate the thought experiment, we first consider the difference in the Boyd ideology scores between the state with the most liberal (Hawaii; -0.3) and most conservative (Nebraska; +0.4) district court judges over our sample period. Over this sample period, Supreme Court ideology shifted by +0.4 points. Thus, the effect of this shift on district court rulings in Hawaii can be calculated as

$$-2 \text{ (coefficient)} \cdot 0.4 \text{ (shift at Supreme Court)} \cdot -0.7 \text{ (Hawaii - Nebraska)} = 0.56.$$

District court rulings in Hawaii become more conservative by 0.56 points relative to district court rulings in Nebraska (measured on the scale between -1 and 1 applied in the Carp-Manning database). Assuming that district court rulings in Nebraska were unaffected by the shift in Supreme Court ideology, the conservative shift in district court rulings is tantamount to an increase of 23 (56/2) percentage points in the share of pro-business rulings in the U.S. District Court of Hawaii between 1978 and 2011.

Next we want to consider the nationwide effect of the conservative shift in Supreme Court ideology. To do so, we need a measure of average district court ideology (unweighted average, population weighted average, unweighted median, population weighted median). In the following we use the population weighted average (-0.067) which lies between the upper bound of the unweighted average (-0.037) and the lower bound of the population weighted median (-0.075 in California). Using the same calculation as above, this implies a conservative shift of

$$-2 \text{ (coefficient)} \cdot 0.4 \text{ (shift at Supreme Court)} \cdot -0.467 \text{ (Average - Nebraska)} = 0.3736$$

points in conservative rulings and thus an increase in the share of pro-business rulings of 18.5 percentage points. Repeating this exercise for our other four main variables gives

$$\begin{aligned}
\text{Unemployment} &: +0.0705 \cdot 0.4 \cdot (-0.476) = -0.0134 \\
\text{Wage} &: +0.1739 \cdot 0.4 \cdot (-0.476) = -0.0331 \\
\text{Union} &: +0.1305 \cdot 0.4 \cdot (-0.476) = -0.0248 \\
\text{Routine} &: +0.0633 \cdot 0.4 \cdot (-0.476) = -0.0121 \\
\text{Inequality} &: -0.3674 \cdot 0.4 \cdot (-0.476) = +0.0700
\end{aligned}$$

Thus, our empirical results suggest that the conservative shift in Supreme Court ideology between 1978 and 2011 approximately accounted for an increase of 18.5 percentage points in the share of pro-business rulings at district courts, a decrease of about 1 percentage point in the unemployment rate, 3 percentage points in the average hourly wage rate, 2.5 percentage points in union coverage and 1 percentage point in the routine employment share, as well as an increase of 7 percentage points in the 90/10 income ratio.

Robustness of the Results Again, we perform several checks to test the robustness of our findings. See C.4 for a detailed description. Specifically, we vary the set of included controls in order to illustrate that our results are not driven by the inclusion or exclusion of certain control variables, include controls for state demographics for consistency with the rulings regressions presented in Section 4.3 and control for pre-sample trends. All of these checks support our results.

We want to make sure that our results actually reflect the interaction between the trend in Supreme Court ideology and district court ideology and not the effects of other aggregate trends correlated with Supreme Court ideology in interaction with state characteristics which are correlated with district court ideology. For example, the literature discusses that import competition has affected the labor market most strongly where the manufacturing employment share is high. Similarly, falling computer capital prices can be expected to unfold their strongest effects where routine employment shares are high. Further, a Republican presidency may affect the labor market in blue states differently than in red states. To corroborate our results, we run regressions where we additionally include interaction terms between district court ideology and the alternative aggregate time-variant variables or between Supreme Court ideology and the alternative state-specific time-invariant variables. Despite the inclusion of these additional interaction terms, our main interaction term remains highly significant and quantitatively close to the results of the baseline specifications.

Finally, one could potentially argue that our results are driven by a conservative shift of the legislation since the late 1970s. However, the data does not support this view. First, both the ideology score of the U.S. Senate and the House of Representatives display a clearly liberal trend between 1981 and 1994, see Figure 4.7, and restricting our analysis to this time period leads to very similar results. Second, the Poole-Rosenthal scores compiled by Lewis et al. (2020) unambiguously show a liberal trend among Democrats and a conservative trend among Republicans in both the Senate and the House since at least 1981. This additionally rules out the possibility that our results are driven by Democrats becoming more conservative since the late 1970s. Nevertheless, we cannot rule out the possibility that Democrats have become more conservative concerning economic issues and more liberal in other dimensions with absolute certainty.

4.4.2 Explanation

In this section, we extend the canonical search and matching model presented in Michaillat (2012) by including the possibility of wrongful-termination lawsuits. To keep the model simple, lawsuits are introduced in a way that proceeds analogously to standard firing costs. The purpose of this exercise is to theoretically evaluate the economic effects of a conservative shift of ideological leanings of the judiciary. We confirm that our empirical findings can be rationalized in this simple framework, which provides a clear first indication that the reduced threat of wrongful-termination lawsuits – working through an erosion of workers bargaining position – is a potential driving force.

Labor Market

The model is populated by a unit mass of risk-neutral workers that can either be employed or unemployed and searching for a job.[21] On the labor market, a continuum of firms $i \in [0, 1]$ hire workers by posting vacancies. Existing worker-firm matches are destroyed at the exogenous rate s, representing voluntary quits. Newly separated workers begin searching for a job in the

[21] There is no saving technology, which implies that workers consume their entire income in each period.

next period. The number of unemployed workers is given by

$$u_t = 1 - (1 - s)n_t$$

and the number of employed workers evolves according to

$$n_t = (1 - s)n_{t-1} + h_t.$$

h_t is the number of new matches, which is given by the constant-returns Cobb-Douglas matching function

$$h_t = \mu u_t^{\eta} v_t^{1-\eta},$$

where μ is the matching efficiency and η is the elasticity of the matching function with respect to the number of unemployed workers. The labor market tightness is defined as $\theta \equiv v_t/u_t$, such that the job-finding probability of a worker is given by $f(\theta_t) = h_t/u_t$ and the job-filling probability for a firm is $q(\theta_t) = h_t/v_t$. The cost of opening a vacancy is c and there is no randomness on the firm side. It follows that a firm can hire a new worker with certainty by opening $1/q(\theta_t)$ vacancies.

Firms

The setting allows for the existence of a representative firm. The real profit of this firm is given by

$$\pi_t = g(n_t) - w_t n_t - \frac{c}{q(\theta_t)} h_t,$$

where $g(n_t) = n_t$ is the production function and w_t are wages. As the production function implies that the Nash-bargained wages will not depend on the number of employed workers, the first order condition for employment is

$$1 = w_t + \frac{c}{q(\theta_t)} - \delta(1 - s)\mathbb{E}_t \left[\frac{c}{q(\theta_{t+1})} \right],$$

where δ is the discount factor and c denotes vacancy posting costs. The firm hires new workers until the marginal product of labor and the discounted costs of hiring next period are equal to the marginal cost of labor, i.e., the wage and the hiring cost.

Wage Bargaining

As is standard in most of the search and matching literature, wages are renegotiated in every period and determined as the solution of a generalized Nash bargaining problem. For simplicity, we assume that new workers are paid the same wage as incumbent workers and only enter wage negotiations in the next period.[22] It follows that for a worker the value of being employed is

$$W_t = w_t + \delta \mathbb{E}_t \left[(1-s)W_{t+1} + sU_{t+1}\right]$$

and the value of being unemployed is

$$U_t = \delta \mathbb{E}_t \left[(1-f(\theta_{t+1}))U_{t+1} + f(\theta_{t+1})W_{t+1}\right].$$

The difference between these two value functions then gives the worker's surplus from a successful renegotiation. We explicitly assume that the costs of lawsuits are lost to the worker-firm pair (think of a firing cost as opposed to a severance payment from the firm to the worker). This choice is based on two observations. First, compared to the legal fees and court fees on both sides, actual payments from firms to workers make up a relatively small part of the costs of employee lawsuits according to the 2017 Hiscox Guide to Employee Lawsuits. Second, as the settlement payment is meant to compensate the employee for forgone earnings and emotional damage due to illegal employer behavior, it would be misleading to include these payments in the worker's value function.

On the firm side, an unsuccessful wage renegotiation and a subsequent termination of the match entails the risk of a wrongful-termination lawsuit.[23] Thus, the firms' surplus from a successful renegotiation is the hiring cost per worker $c/q(\theta_t)$, plus the expected costs of a wrongful-termination lawsuit $\mathbb{L}$, times the probability of losing the lawsuit (1-ρ), where ρ is the probability of a pro-business ruling.[24] Because the possibility of losing a lawsuit enters a firm's value function as a cost, it facilitates exposition to summarize judicial ideology by the loss probability from the perspective of firms in this model. Denoting the bargaining power of the worker with β, Nash bargaining solves

$$W_t - U_t = \frac{\beta}{1-\beta}\left[\frac{c}{q(\theta_t)} + (1-\rho)\cdot\mathbb{L}\right].$$

The resulting steady state wage schedule is

$$w = \frac{\beta(1-s-f(\theta))}{1-\beta}\left[\frac{c}{q(\theta)} + (1-\rho)\cdot\mathbb{L}\right],$$

which depends positively on labor market tightness and negatively on the share of pro-business rulings.

[22] This assumption is made in order to facilitate representation. The wages for new and incumbent workers would be different otherwise. The results are not affected by this assumption.

[23] Note, that with Nash bargaining there will be no lawsuits in equilibrium. All of the results will be entirely driven by the threat of a potential lawsuit.

[24] In the data, rulings are either coded as liberal ($r = -1$) or as conservative ($r = 1$). Using the same coding in our model in Section 4.3, the probability of a pro-business ruling ρ is linked to the average ruling r from the model through the definition $\rho = (1+r)/2$.

Table 4.8. Parameter Calibration

Symbol	Interpretation	Value	Source/Target
δ	Discount factor	0.999	5% Annual discount rate
s	Separation rate	0.0095	Michaillat (2012) using JOLTS
μ	Matching efficiency	0.233	Michaillat (2012) using JOLTS
η	Unemployment-elasticity of matching	0.5	Petrongolo and Pissarides (2001)
c	Vacancy posting costs	0.32	0.32 x steady state wage
β	Bargaining power of workers	0.5	Shimer (2005)
ρ	Probability of pro-business ruling	0.55	Carp and Manning (2016)
$\mathbb{L}$	Cost of lost lawsuit	0.78	6.4% unemployment rate

Theoretical Effects of More Pro-Business Rulings

Now that we have derived both the first order condition for employment and the wage schedule, we consider analytically the effects of an increase in the probability of pro-business decisions on labor market outcomes in our simple model.

As the lower expected average cost of a lawsuit reduces the employer's surplus from wage negotiations, the employer is able to enforce lower wages. Intuitively, the employer can credibly claim that the continuation of the worker-firm relationship is less valuable, as a lawsuit upon termination hurts the firm less. The effect of an increase in the share of pro-business rulings ρ on the steady state wage is given by

$$\frac{\partial w}{\partial \rho} = -\frac{\beta(1-s-f(\theta))\mathbb{L}}{(1-\beta)+\beta\frac{\partial f(\theta)}{\partial \theta}\frac{\partial \theta}{\partial w}\left(\frac{c}{q(\theta)}+(1-\rho)\mathbb{L}\right)}.$$

The increase in ρ reduces labor costs and firms will post more vacancies, which slightly attenuates the negative effect of ρ on the wage rate.

The effect of a wage increase on the steady state labor market tightness θ is given by

$$\frac{\partial \theta}{\partial w} = -\frac{1}{\eta}\left[\frac{1-w}{[1-\delta(1-s)]\,c}\right]^{\frac{1-\eta}{\eta}}\frac{1}{[1-\delta(1-s)]\,c}.$$

Consequently, the wage decrease triggered by the increasing share of pro-business rulings increases the labor market tightness and therefore increases the job-finding rate. Using the Beveridge curve, steady state employment increases by

$$\frac{\partial n}{\partial \theta} = \frac{1}{((1-s)+s/f(\theta))^2}\frac{s}{f(\theta)^2}\frac{\partial f(\theta)}{\partial \theta}.$$

Table 4.9. Theoretical Effects of Pro-Business Rulings

	Probability of a pro-business ruling increases by...		
	5 ppt.	10 ppt.	15 ppt.
Unemployment	-0.35 ppt.	-0.66 ppt.	-0.95 ppt.
Employment	+0.38 ppt.	+0.67 ppt.	+0.95 ppt.
Job-finding rate	+3.71 ppt.	7.43 ppt.	11.17 ppt.
Wage	-0.06 ppt.	-0.12 ppt.	-0.17 ppt.

Note: The entries in this table represent percentage point changes in a specific labor market outcome following an increase of 5, 10, and 15 percentage points in the probability of a pro-business ruling.

Quantitative Evaluation

In this section, we calibrate the model to match quarterly U.S. data for the time period between 1978 and 2011. The calibrated model is used to quantitatively evaluate the effect of an increase in the share of pro-business rulings in the model.

Calibration In calibrating the model we follow the calibration strategy used in Michaillat (2012). Table 4.8 lists the parameter values and the source that encourages the specific choice. The discount factor is set to $\beta_c = 0.999$, to match an annual discount rate of 5$\%$. The parameter values for the separation rate s and the matching efficiency μ are taken from Michaillat (2012), who provides estimates based on the Job Opening and Labor Turnover Survey (JOLTS). The calibration targets for the matching elasticity η and for the bargaining power β are standard in the literature (cf. Petrongolo and Pissarides, 2001; Shimer, 2005). Following Michaillat (2012), who bases his estimates on studies by Barron et al. (1997) and Silva and Toledo (2009), the vacancy posting costs c are calibrated to 32$\%$ of the steady state wage. The probability of a pro-business ruling ρ is calibrated to match the average share of pro-business rulings in district courts in the Carp-Manning database. Finally, we calibrate the cost of a lost lawsuit $\mathbb{L}$ to 0.78 (2.4 $\times$ a workers monthly steady state wage) in order to match the average unemployment rate of 6.4$\%$ over the time period between 1978 and 2011.

Simulation Results We use the calibrated model to assess the theoretical effect of an increase in the share of pro-business rulings ρ. The results are summarized in Table 4.9. A ten percentage point increase in the probability of winning a lawsuit lowers the simulated unemployment rate by about 0.66 percentage points (compared to a decrease of 0.7 percentage points in the data).[25]

[25]Due to the increased labor market tightness, wage changes are significantly smaller compared to our empirical results. However, in the data wage decreases are likely magnified by the decreasing union coverage of workers which the model abstracts from. While an increase of 7.4 percentage points in the job-finding rate appears

4.5 Conclusion

In this paper, we have documented substantial economic effects of ideological tendencies in court rulings. In a first stage, we have shown that the share of conservative rulings has increased in states with rather liberal district courts relative to states with rather conservative district courts following the shift of the Supreme Court towards the conservative end of the ideological spectrum since the late 1970s. In a second stage, we have exploited these differential effects on U.S. states in order to identify the economic impact of a conservative shift in ideological tendencies of the judiciary. We find that an increase in the share of conservative rulings substantially increases the employment rate and promotes labor market fluidity but also contributes to wage stagnation, job market polarization, deunionization, and rising income inequality.

stark at first glance, keep in mind that the model is calibrated to quarterly frequency, whereas we look at weekly job-finding rates in the data.

5 Concluding Remarks

The U.S. labor market has undergone several important developments over the last decades. In each chapter of this thesis, I have shed light on one specific aspect of changing labor markets: technical change, selective hiring, and judicial ideology.

In Chapter 2, Tobias Föll and I provide a joint theory of polarization and deunionization. We empirically show that the decline in unionization rates over the last decades is more pronounced in U.S. states with a larger decline in the employment share of routine-intensive occupations. In a search and matching model that endogenizes both workers' occupational and union-membership decisions, we show that routine-biased technical change not only generates polarization but also deunionization. While the overall effect of deunionization on income inequality seems to be quite small, repercussions for low- to middle-skilled previously unionized workers are large. We argue that even small policy changes could potentially lead to large effects on income inequality for these workers.

In Chapter 3, I document both empirically and analytically a connection between involuntary part-time employment and workers' job mobility in the U.S. While involuntary part-time workers move on average more often to new jobs than unrestricted workers, their job mobility is characterized by a particularly strong trend decline over the last two decades. This development can be related to changes in the selectivity with which firms recruit workers and a scarring effect of involuntary part-time work. In a search and matching model with on-the-job search, I show that when a worker's current employment status matters, and firms become more selective when recruiting, having worked part-time leads to a reduction in the rate of finding full-time employment. My findings suggest that the ongoing policy debate on encouraging workers' job mobility should be extended by incorporating issues of involuntary part-time employment.

In Chapter 4, Christian Bredemeier, Tobias Föll, and I document substantial labor market effects of ideological tendencies. By using heterogenous effects of ideological shifts of the U.S. Supreme Court on U.S. district court rulings, we show empirically that an increase in the share of conservative rulings substantially increases the employment rate but decreases pay as well as other measures of job quality and increases inequality. We rationalize our main empirical results in a search and matching model with wrongful-termination lawsuits. Our results indicate that, due to lifetime appointments, decisions regarding the composition of the judiciary possible influence economic perspectives of household for decades.

A Appendix to Chapter 2

A.1 First Order Conditions of Firms

Defining the value of a marginal worker in an abstract non-routine cognitive occupations for a firm as J_a, the first-order conditions for hiring and for vacancy posting are given by

$$\begin{aligned} c_a &= \mu_a q_a \\ \mu_a &= \beta J_{a,+1}, \end{aligned}$$

where μ_a is the Lagrange-multiplier on the employment constraint for workers in abstract occupations. The corresponding value of a marginal worker in abstract non-routine cognitive occupations is

$$J_a = p_{Z_a} - \mathbb{1}_u w_a^u - (1 - \mathbb{1}_u) w_a^n + (1 - s_a)\beta J_{a,+1}.$$

Defining the value of a marginal worker with ability η in a routine occupation for a firm as $J_r(\eta)$, the first-order conditions for hiring workers in routine tasks and for vacancy posting are given by

$$\begin{aligned} c_r &= \mu_r q_r \\ \mu_r &= \beta J_{r,+1}, \end{aligned}$$

where μ_r is the Lagrange-multiplier on the employment constraint for a worker in routine occupations. The corresponding value of a marginal worker with ability η in routine occupations is

$$\begin{aligned} J_r &= p_{Z_r} \overline{y_r} - \mathbb{1}_u \overline{w_r^u} - (1 - \mathbb{1}_u)\overline{w_r^n} + (1 - s_r)\beta J_{r,+1}, \\ &\text{with } y_r(\eta) = \frac{\partial Z_r}{\partial L_r(\eta)} = \eta(1-\mu)^\sigma \left[(1-\mu)^\sigma + (\mu k)^\sigma\right]^{\frac{1}{\sigma}-1} \text{ and } k \equiv \frac{K}{\int_{\eta_m}^{\bar{\eta}} \eta L_r(\eta)}, \end{aligned}$$

where $\overline{y_r}$ is the expected marginal product of a routine worker, $\overline{w_r^u}$ is the expected union wage, and $\overline{w_r^n}$ the expected non-union wage. The average marginal product and the average wages are used here, as firms are unable to condition their job search on the ability level η.

Defining the value of a marginal worker with ability η in a non-routine manual occupation for a firm as J_m, the first-order conditions for hiring workers in manual tasks and for vacancy posting are given by

$$c_m = \mu_m q_m$$
$$\mu_m = \beta J_{m,+1},$$

where μ_m is the Lagrange-multiplier on the employment constraint for worker in manual occupations. The corresponding value of a marginal worker with ability η in manual occupations is

$$J_m = p_{Z_m} - \mathbb{1}_u w_m^u - (1 - \mathbb{1}_u) w_m^n + (1 - s_m)\beta J_{m,+1}.$$

A.2 Job Creation Conditions

The job creation conditions are given by

$$\frac{c_i}{q_i} = \beta J_{i,+1}$$
$$\text{with } i = a, r, m.$$

Together with the values of marginal workers for firms, it follows that

$$\frac{c_a}{q_a} = \beta \left[p_{Z_a} - \mathbb{1}_{u,+1} w_a^u - (1 - \mathbb{1}_{u,+1}) \, w_a^n + (1 - s_a) \frac{c_a}{q_{a,+1}} \right]$$
$$\frac{c_r}{q_r} = \beta \left[p_{Z_r} \overline{y_r} - \mathbb{1}_{u,+1} \overline{w_r^u} - (1 - \mathbb{1}_{u,+1}) \, \overline{w_r^n} + (1 - s_r) \frac{c_r}{q_{r,+1}} \right]$$
$$\frac{c_m}{q_m} = \beta \left[p_{Z_m} - \mathbb{1}_{u,+1} w_m^u - (1 - \mathbb{1}_{u,+1}) \, w_m^n + (1 - s_m) \frac{c_m}{q_{m,+1}} \right].$$

As we are mainly interested in the long-run effect of routine-biased technical change on the economy and on the wage bargaining regimes, we focus on the steady state of the economy. The steady state job creation conditions are given by

$$\frac{c_a}{q_a} = \beta \left[p_{Z_a} - \mathbb{1}_u w_a^u - (1 - \mathbb{1}_u) \, w_a^n + (1 - s_a) \frac{c_a}{q_a} \right] \tag{A.1}$$

$$\frac{c_r}{q_r} = \beta \left[p_{Z_r} \overline{y_r} - \mathbb{1}_u \overline{w_r^u} - (1 - \mathbb{1}_u) \, \overline{w_r^n} + (1 - s_r) \frac{c_r}{q_r} \right] \tag{A.2}$$

$$\frac{c_m}{q_m} = \beta \left[p_{Z_m} - \mathbb{1}_u w_m^u - (1 - \mathbb{1}_n) \, w_m^n + (1 - s_m) \frac{c_m}{q_m} \right]. \tag{A.3}$$

A firm hires workers of each type and each ability level η until the costs of labor are equal to the discounted expected marginal product.

A.3 Derivation of Wages

In this section we derive the non-union wages in the model. The surplus sharing rules are given by

$$W_i^n(\eta) - U_i(\eta) = \frac{\gamma^i}{1 - \gamma^i} J_i^n(\eta),$$
$$\text{with } i = a, r, m.$$

Abstract Workers

After replacing the value function, the Nash sharing rule for abstract workers is

$$\begin{aligned} & w_a^n + \beta \left[(1 - s_a) W_a^n + s_a U_a \right] - z_a - \beta [(1 - f_a) U_a^n + f_a W_a^n \} \\ & = \frac{\gamma^a}{1 - \gamma^a} \left[p_{Z_a} - w_a^n + (1 - s_a) \beta J_a^n \right]. \end{aligned}$$

By rearranging, we get

$$\begin{aligned} w_a^n = {} & \gamma^a p_{Z_a} + (1 - \gamma^n) z_a + \gamma^a (1 - s_a) \beta J_a^n \\ & + (1 - \gamma^a) \beta \left[f_a \left(W_a^n - U_a^n \right) - (1 - s_a) \left(W_a^n - U_a^n \right) \right]. \end{aligned}$$

Using the job creation condition (A.1), $\frac{c_a}{q_a} = \beta J_{a,+1}^n$, the surplus sharing rule can be written as

$$(1 - \gamma^a) \left(W_a^n - U_a^n \right) = \gamma^a J_a^n = \gamma^a \frac{c_a}{\beta q_a}.$$

The wage equation for abstract workers is given by

$$w_a^n = \gamma^a p_{Z_a} + \gamma^a c_a \theta_a + (1 - \gamma^a) z_a.$$

Routine Workers

After replacing the value function, the Nash sharing rule for routine workers of ability level η is

$$\begin{aligned}&w_r^n(\eta) + \beta\left[(1-s_r)W_r^n(\eta) + s_r U_r(\eta)\right] - z_r(\eta) - \beta[(1-f_r)U_r^n(\eta) + f_r W_r^n(\eta)\}\\&= \frac{\gamma^r}{1-\gamma^r}\left[p_{Z_r} y_r(\eta) - w_r^n(\eta) + (1-s_r)\beta J_r^n\right].\end{aligned}$$

By rearranging, we get

$$\begin{aligned}w_r^n(\eta) &= \gamma^r p_{Z_r} y_r(\eta) + (1-\gamma^r) z_r(\eta) + \gamma^r(1-s_r)\beta J_r^n\\&\quad + (1-\gamma^r)\beta\left[f_r\left(W_r^n(\eta) - U_r^n(\eta)\right) - (1-s_r)\left(W_r^n(\eta) - U_r^n(\eta)\right)\right].\end{aligned}$$

Using the job creation condition (A.2), $\frac{c_r}{q_r(\eta)} = \beta J_r^n(\eta)$, the surplus sharing rule can be written as

$$(1-\gamma^r)\left(W_r^n(\eta) - U_r^n(\eta)\right) = \gamma^r J_r^n(\eta) = \gamma^r \frac{c_r}{\beta q_r}.$$

The wage equation for routine workers is given by

$$w_r^n(\eta) = \gamma^r p_{Z_r} y_r(\eta) + \gamma^r c_r \theta_r + (1-\gamma^r) z_r(\eta).$$

Manual Workers

After replacing the value function, the Nash sharing rule for manual workers is

$$\begin{aligned}&w_m^n + \beta\left[(1-s_m)W_m^n + s_m U_m\right] - z_m(\eta) - \beta[(1-f_m)U_m^n + f_m W_m^n\}\\&= \frac{\gamma^m}{1-\gamma^m}\left[p_{Z_m} - w_m^n + (1-s_m)\beta J_m^n\right].\end{aligned}$$

By rearranging, we get

$$\begin{aligned}w_m^n &= \gamma^m p_{Z_m} + (1-\gamma^m) z_m(\eta) + \gamma^m(1-s_m)\beta J_m^n\\&\quad + (1-\gamma^m)\beta\left[f_m\left(W_m^n - U_m^n\right) - (1-s_m)\left(W_m^n - U_{m,+1}^n\right)\right].\end{aligned}$$

Using the job creation condition (A.3), $\frac{c_m}{q_m} = \beta J_m^m$, the surplus sharing rule can be written as

$$(1-\gamma^m)\left(W_m^n - U_m^n\right) = \gamma^m J_m^n = \gamma^m \frac{c_m}{\beta q_m}.$$

The wage equation for manual workers is given by

$$w_m^n = \gamma^m p_{Z_m} + \gamma^m c_m \theta_m + (1-\gamma^m) z_m(\eta).$$

A.4 Union Surplus

In this section we derive the industrial union surplus. The derivation of the craft union surplus proceeds analogously. The first order condition in the collective bargaining problem is given by

$$\begin{aligned}
&\sum_i \int_{\underline{\eta}}^{\bar{\eta}} L_i(\eta) \left[W_i^u(\eta) - W_i^{u,s}(\eta)\right] \mathrm{d}\,\eta \\
&= \frac{\gamma^u}{1-\gamma^u} \sum_i \Big\{ p_{Z_i} Z_i - p'_{Z_i} Z'_i - \int_{\underline{\eta}}^{\bar{\eta}} L_i(\eta) w_i^u(\eta) \,\mathrm{d}\,\eta \Big\}, \\
&\text{with } i = r, m.
\end{aligned}$$

After replacing the value function and using the job creation conditions (A.2) and (A.3), the Nash sharing rule is

$$\begin{aligned}
&\sum_i \int_{\underline{\eta}}^{\bar{\eta}} L_i(\eta) \left[w_i^u(\eta) - w_i^{u,s}(\eta)\right] \mathrm{d}\,\eta \\
&= \frac{\gamma^u}{1-\gamma^u} \sum_i \Big\{ p_{Z_i} Z_i - p'_{Z_i} Z'_i - \int_{\underline{\eta}}^{\bar{\eta}} L_i(\eta) w_i^u(\eta) \,\mathrm{d}\,\eta \Big\}.
\end{aligned}$$

By rearranging, we get

$$\begin{aligned}
&\gamma^u \sum_i \left(p_{Z_i} Z_i - p'_{Z_i} Z'_i\right) + (1-\gamma^u) \sum_i \int_{\underline{\eta}}^{\bar{\eta}} L_i(\eta) w_i^{u,s}(\eta) \,\mathrm{d}\,\eta \\
&= \gamma^u \sum_i \int_{\underline{\eta}}^{\bar{\eta}} L_i(\eta) w_i^u(\eta) \,\mathrm{d}\,\eta + (1-\gamma^u) \sum_i \int_{\underline{\eta}}^{\bar{\eta}} L_i(\eta) w_i^u(\eta) \,\mathrm{d}\,\eta.
\end{aligned}$$

Thus, the total union surplus is given by

$$\begin{aligned}
S^u &= \sum_i \int_{\underline{\eta}}^{\bar{\eta}} L_i(\eta) w_i^u(\eta) \,\mathrm{d}\,\eta \\
&= \gamma^u \sum_i \left(p_{Z_i} Z_i - p'_{Z_i} Z'_i\right) + (1-\gamma^u) \sum_i \int_{\underline{\eta}}^{\bar{\eta}} L_i(\eta) w_i^{u,s}(\eta) \,\mathrm{d}\,\eta \\
&\text{with } i = r, m.
\end{aligned}$$

A.5 Theoretical Evaluation of the Main Mechanisms

The arguments in this section proof Propositions 1 and 2 of Section 2.5.7.

A.5.1 Polarization

Routine-biased technical change is modeled as a drop in p_k, the relative price of computer capital. As we are concerned with the incentives of previous routine workers to switch to manual occupations, we consider the effects of a decrease in p_k before any employment adjustment occurs. Thus, L_a, L_r, and L_m are constant.

Note that the decrease in the relative price only affects the intermediate firm producing Z_r directly. From the first order condition with respect to computer capital

$$\frac{\partial Z_r}{\partial K} = \mu^{\sigma} \left[\left(\frac{1-\mu}{k} \right)^{\sigma} + \mu^{\sigma} \right]^{\frac{1}{\sigma}-1}$$

it follows that K increases if and only if computer capital and workers performing routine tasks are substitutes, i.e, if $\sigma > 0$.[1] The increasing computer capital stock increases the production of the intermediate good Z_r.

Keep in mind that an unemployed routine worker switches occupations if $U_m(\eta) > U_r(\eta)$. Thus, given that unemployment benefits and separation rates are not affected by the drop in capital prices, the two variables driving changes in the incentives are wages and job-finding rates. From the wage equations and job creation conditions for both types of occupations it immediately follows that both variables of interest are driven by changes in the marginal productivity of the respective workers.

As the relevant elasticities (the elasticity of the wage with respect to productivity and labor market tightness and the elasticity of the job-finding rate with respect to productivity and wages) are identical for both types of occupations, it remains to show that the marginal productivity of manual workers increases by more compared to the marginal productivity of routine workers due to routine-biased technical change.

The relative marginal productivity of routine workers compared to manual workers is given by

$$\frac{p_{Z_r} y_r(\eta)}{p_{Z_m}} = \eta(1-\alpha)(1-\mu)^{\sigma} \left(\frac{A^{1+\frac{1}{\rho}}}{A_m} \right)^{\rho} \left(\frac{Z_a^{\frac{\alpha\rho}{\rho-1}}}{Z_m} \right)^{\rho-1}$$
$$\left((1-\mu) \int_{\eta_m}^{\bar{\eta}} \eta L_r(\eta) \, \mathrm{d}\, \eta \right)^{\sigma-1} Z_r^{(1-\alpha)\rho-\sigma}.$$

Thus, the relative productivity of routine workers decreases in Z_r, if $\sigma > (1-\alpha)\rho$, which

[1] Since the computer capital stock can be adjusted instantaneously and without frictions, an increase in K before occupational switches occur is in line with the model setup.

proofs Proposition 1. Intuitively, in order for routine-biased technical change to increase the incentives for occupational switches, capital and routine tasks need to be substitutes and they need to be better substitutes than routine and manual tasks in the production of the final good.

A.5.2 Voting Incentives

A manual worker inside a unionized firm votes in favor of collective bargaining coverage, if the value of being a manual worker in a unionized firm is larger than the value of being a worker in a non-unionized firm, i.e., if $W_m^u > W_m^n$. As in Appendix A.5.1, the relevant variables are again the wages and the job-finding rates. As the marginal productivity of a manual worker is independent of the union status of the firm, relative changes in the job-finding rates are entirely driven by relative wage changes. Thus, it suffices to show that the non-union wage rate for manual workers increases relative to the union wage rate.[2]

Using the equation for the union surplus (2.8), the union wage schedule (2.6), and the non-union wage for manual workers (2.5), the relative union wage for a manual worker is given by[3]

$$\frac{w_m^u}{w_m^n} = \frac{\left[\gamma^u(p_{Z_m}Z_m - p'_{Z_m}Z'_m) + \gamma^u(p_{Z_r}Z_r - p'_{Z_r}Z'_r)\right]/(L_m + L_r)}{\gamma^m p_{Z_m} + \gamma^m c_m \theta_m^n}.$$

Using the production functions, this expression can be rewritten as

$$\frac{w_m^u}{w_m^n} = \frac{\left[\gamma^u p_{Z_m}Z_m\right]/(L_m + L_r)}{\gamma_m p_{Z_m} + \gamma_m c_m \theta_m^n} + \frac{\left[\gamma^u(p_{Z_r}Z_r - p'_{Z_r}Z'_r)\right]/(L_m + L_r)}{\gamma_m p_{Z_m} + \gamma_m c_m \theta_m^n}. \tag{A.4}$$

First, following the arguments in Appendix A.5.1, routine-biased technical change implies an increase in Z_r and thus an increase in the marginal productivity of manual workers, p_{Z_m}. Second, note that the effect of routine-biased technical change on the first term only depends on the elasticity of this term with respect to p_{Z_m}. Combining the job creation condition (A.3) and the wage for manual workers (2.5) yields

$$((1/\beta) - 1 + s_m)c_m\Psi_m(\theta_m^n)^\eta + c_m\gamma^m\theta_m^n = (1 - \gamma^m)p_{Z_m}.$$

From this expression it is easy to see that the elasticity of θ_m^n with respect to p_{Z_m} is larger than one. Next, we use that for two functions f and g the elasticity of $(g + f)$ is given by $\epsilon_{f+g} = \frac{f\epsilon_f + g\epsilon_g}{f+g}$ to establish that the elasticity of the non-union wage of manual workers is larger than one. This directly implies that the first term of equation (A.4) decreases in p_{Z_m}.

Intuitively, routine-biased technical change increases the productivity of and therefore the

[2] Note that the positive effect of a wage increase on the value function is not offset by a decrease in the job-finding rate.

[3] Since w_i^u and $z_i(\eta)$ are both unaffected by routine-biased technical change and set to zero in the simulation, they are left out in order to facilitate representation.

demand for manual workers. The non-union wage for manual workers increases as both the productivity and the labor market tightness increase. The union wage for manual workers increases by less, as the different outside options in the two bargaining regimes imply that the greater labor market tightness does not affect the collective bargaining.

For the second term in equation (A.4) it holds that

$$\frac{Z_r}{Z'_r} = \left[1 + \left(\frac{(1-\mu)\int_{\eta_m}^{\bar{\eta}} \eta L_r(\eta)\,\mathrm{d}\,\eta}{\mu K}\right)^{\sigma}\right]^{\frac{1}{\sigma}}.$$

Thus, an increase in K due to routine-biased technical change reduces $\frac{Z_r}{Z'_r}$. After some rearrangement, $\frac{p_{Z_r} Z_r}{p'_{Z_r} Z'r}$ is given by

$$\frac{p_{Z_r} Z_r}{p'_{Z_r} Z'_r} = \frac{[(AZ_a^{\alpha} Z_r^{1-\alpha})^{\rho} + (A_m Z_m)^{\rho}]^{1/\rho} - 1}{[(AZ_a^{\alpha}(Z'_r)^{1-\alpha})^{\rho} + (A_m Z_m)^{\rho}]^{1/\rho - 1}} \left(\frac{Z_r}{Z'_r}\right)^{(1-\alpha)\rho}.$$

Using that $\frac{Z_r}{Z'_r}$ decreases with K, it is straightforward to show that an increase in K reduces $\frac{p_{Z_r} Z_r}{p'_{Z_r} Z'r}$ if routine and manual tasks are substitutes, i.e, if $\rho > 0$.

Taken together, routine-biased technical change reduces the union wage of manual workers relative to the non-union wage of manual workers, if $\rho > 0$. This proofs Proposition 2. This result does not depend on our choice of the union wage schedule, as long as the wage schedule meets the empirical observations of wage compression and non-increasing individual union wage premia in workers' skill level, since the proof also holds if we exchange the union wage of manual workers for the union surplus.

A.6 Empirical Analysis: Robustness Checks

In this section we present several robustness checks: regressions using union coverage as the dependent variable, regressions using the average routine share instead of the initial routine share in our instrument, and unweighted regressions.

The results are summarized in Tables A.1–A.3. Our instrument remains highly statistically significant across all alternative specifications. As was to be expected, union coverage reacts less to falling relative prices for investment goods than union membership.

Table A.1. Regression Results for Unionization Rates – Average Routine Share

	(1)	(2)	(3)	(4)
Capital prices	0.4116***	0.6254***	0.4054***	0.6099***
× routine employment share	(0.0743)	(0.0724)	(0.0702)	(0.0682)
Observations	1116	1116	1116	1116
R^2	0.9870	0.9834	0.9863	0.9822
Industry and occupation controls	yes	yes	no	no
State policy controls	yes	no	yes	no
State legislation controls	yes	no	yes	no
State demographic controls	yes	no	yes	no
Year fixed effects	yes	yes	yes	yes
State fixed effects	yes	yes	yes	yes

Note: Observations are weighted by the average state population over our sample period. The standard errors are reported in parentheses. *** indicates significance at the 1 percent level, ** indicates significance at the 5 percent level, and * indicates significance at the 10 percent level.

Table A.2. Regression Results for Unionization Rates – Unweighted

	(1)	(2)	(3)	(4)
Capital prices	0.1961***	0.1982***	0.1508***	0.1522***
× routine employment share	(0.0422)	(0.0416)	(0.0379)	(0.0403)
Observations	1116	1116	1116	1116
R^2	0.9765	0.9727	0.9753	0.9721
Industry and occupation controls	yes	yes	no	no
State policy controls	yes	no	yes	no
State legislation controls	yes	no	yes	no
State demographic controls	yes	no	yes	no
Year fixed effects	yes	yes	yes	yes
State fixed effects	yes	yes	yes	yes

Note: Observations are weighted by the average state population over our sample period. The standard errors are reported in parentheses. *** indicates significance at the 1 percent level, ** indicates significance at the 5 percent level, and * indicates significance at the 10 percent level.

Table A.3. Regression Results for Union Coverage Rates

	(1)	(2)	(3)	(4)
Capital prices	0.2031***	0.3468***	0.1913***	0.2817***
$\times$ routine employment share	(0.0583)	(0.0578)	(0.0536)	(0.0514)
Observations	1116	1116	1116	1116
R^2	0.9839	0.9802	0.9828	0.9784
Industry and occupation controls	yes	yes	no	no
State policy controls	yes	no	yes	no
State legislation controls	yes	no	yes	no
State demographic controls	yes	no	yes	no
Year fixed effects	yes	yes	yes	yes
State fixed effects	yes	yes	yes	yes

Note: Observations are weighted by the average state population over our sample period. The standard errors are reported in parentheses. *** indicates significance at the 1 percent level, ** indicates significance at the 5 percent level, and * indicates significance at the 10 percent level.

A.7 Data Appendix

In Table A.4 we provide the complete list of control variables used in the regressions in Section 2.3.

Table A.4. List of Control variables

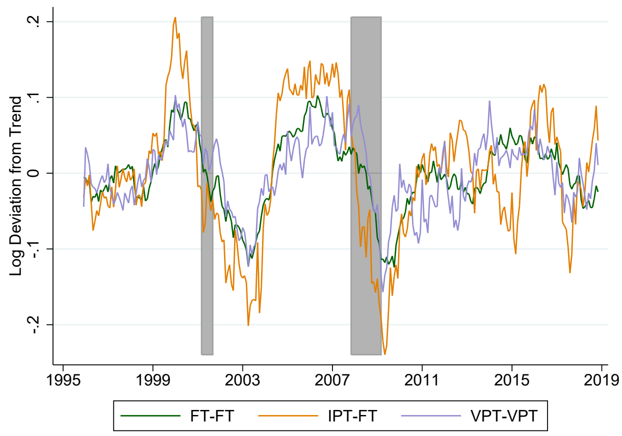
State demographics	
Share of population living in a central city (urban density)	CPS
Share of population living in a city (urban density)	CPS
Share of black population (ethnic composition)	CPS
Share of white population (ethnic composition)	CPS
Shares of population in age groups 16-24; 25-44; 45-54; >55	CPS
Share of workers with each educational level:	CPS
less than high school; high school; some college; college or more	
Share of male population	CPS
Industry-occupation controls	
Shares of workers employed in industry groups:	CPS
construction; manufacturing; transportation, communcations, and other public utilities;	
wholesale and retail trade; services; finance, insurance, and real estate	
Shares of workers employed in occupational groups:	CPS + AD
abstract; routine; manual	
State policy controls	
Minimum wage rate	FRED
Total federal intergovernmental revenue	SLGFD
Total tax burden	TF
State gov. and leg. controls	
State senate majority party	NCLS
(1: Rep., -1: Dem., 0: other/indep./no majority)	
State house majority party	NCLS
(1: Rep., -1: Dem., 0: other/indep./no majority)	
Political party of the governor	NCLS
(1: Rep., -1: Dem., 0: other/indep./no majority)	

Note: AD: Autor and Dorn (2013); CPS: Current Population Survey; FRED: Federal Reserve Economic Data; NCLS: National Conference of State Legislatures; SLGFD: State and Local Government Finance Dataset; TF: Tax Foundation.

B Appendix to Chapter 3

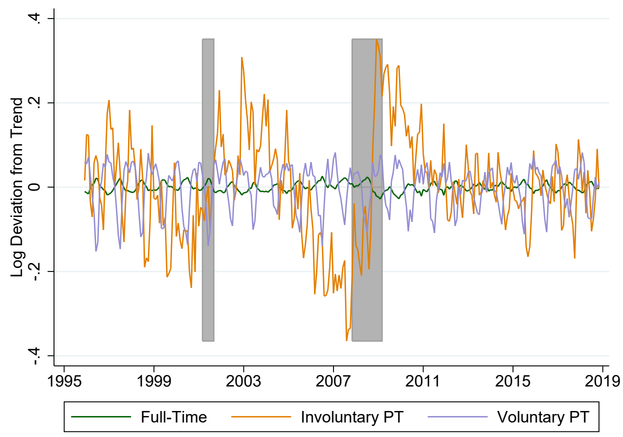
B.1 Empirical Analysis: Additional Results

Figure B.1. Log Deviation of Employment Transitions from Trend, 1996 – 2018



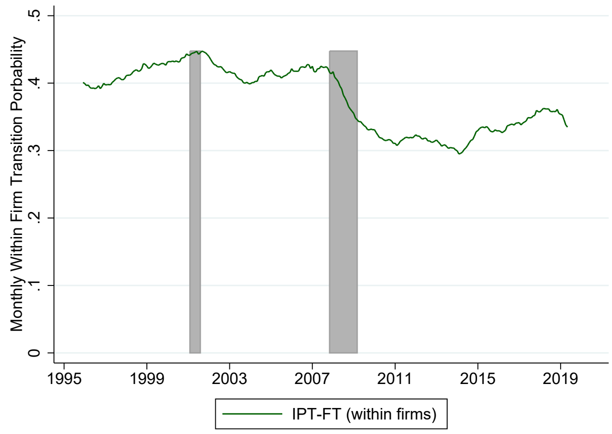
Notes: All flows are constructed using monthly CPS data. I plotted HP-Filtered log monthly data. Grey bars denote NBER recession dates.

Figure B.2. Log Deviation of Employment Shares from Trend, 1996 – 2018



Notes: Shares are constructed using CPS data. I plot HP-Filtered log monthly data. Grey bars denote NBER recession dates.

Figure B.3. Transition Probability within Firms, 1996 – 2018



Notes: All flows are constructed using monthly CPS data. I plot twelve-months moving averages of monthly data. Grey bars denote NBER recession dates.

Table B.1. Changes in Involuntary Part-Time Transition Probabilities by Industry of Origin

	Long Term	2001 Recession	Great Recession
Retail Trade and Services	-57.2%	-29.4%	-39.4%
Non Services	-52.8%	-28.0%	-34.5%

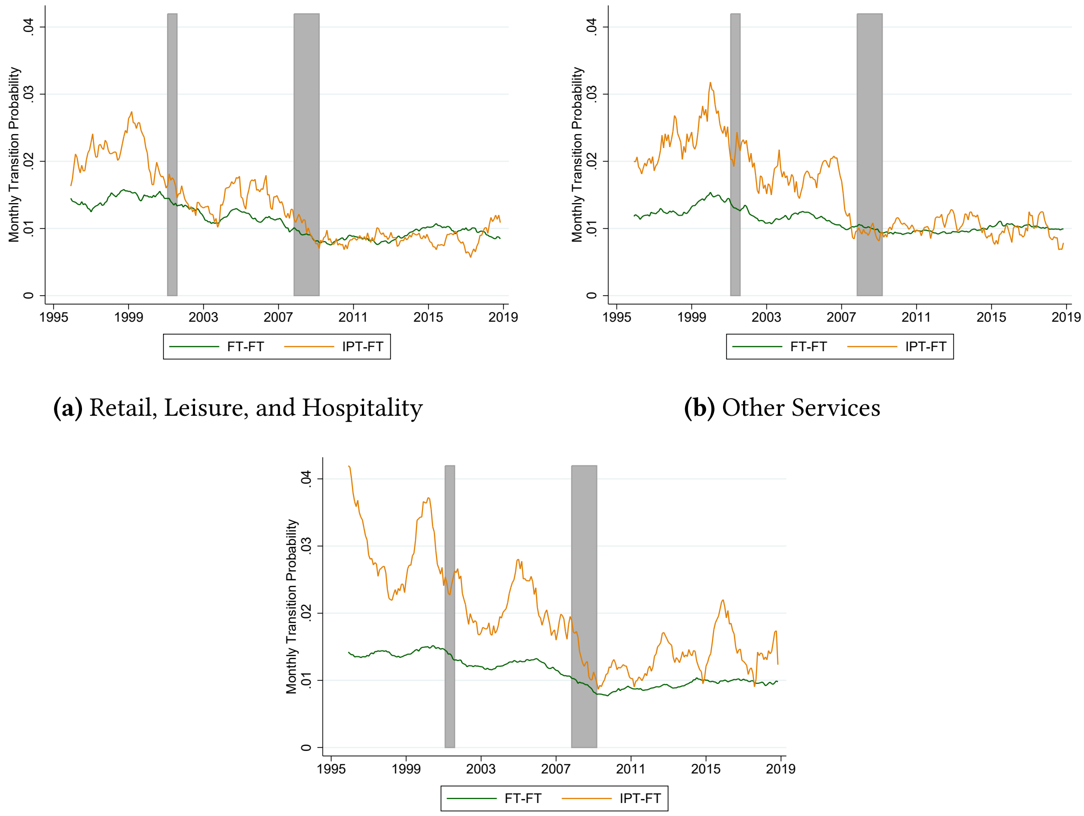
Notes: Monthly CPS data. Transition probabilities are calculated considering the industry category in the origin occupation. Changes are reported between 3 different time periods: before the 2001 Recession from 1996m01-2001m02, between the two Recessions from 2001m12-2007m11 and after the Great Recession from 2009m7-2018m12. Column 1 shows long term changes from before the 2001 Recession to after the Great Recession. Column 2 shows changes for the 2001 Recession. Column 3 shows changes for the Great Recession.

Table B.2. Within Industry Involuntary Part-Time Transition Probabilities

	1996-2001	2001-2007	2009-2018
Retail trade and Services	2.2%	1.4%	0.9%
Other Services	2.3%	1.8%	1.0%
Non Services	2.9%	2.1%	1.4%

Notes: CPS data. Transition probabilities are calculated considering only switches within industries for each category. Averages are reported for 3 different time periods: before the 2001 Recession from 1996m01-2001m02, between the two Recessions from 2001m12-2007m11, and after the Great Recession from 2009m7-2018m12.

Figure B.4. Transition Probability by Job Transition Status within Industries, 1996 – 2018



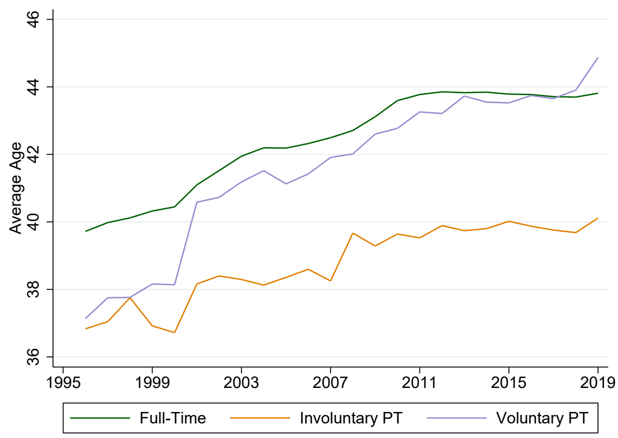
(a) Retail, Leisure, and Hospitality

(b) Other Services

(c) Non Services

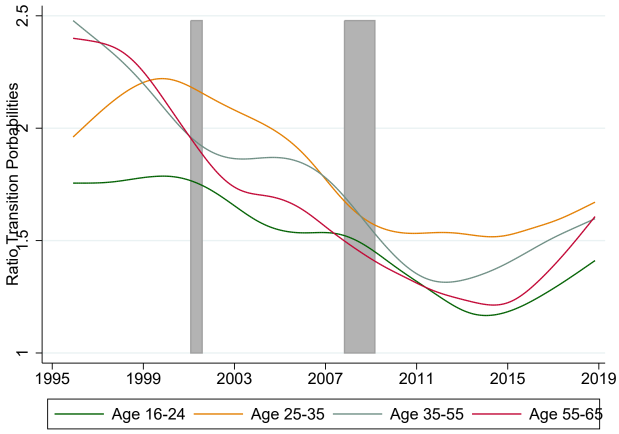
Notes: All flows are constructed using CPS data. I plot twelve-month moving averages of monthly data. Panel (a) shows the job mobility in retail trade, leisure and hospitality. Panel (b) shows the job mobility in educational and health services and professional and business services. Panel (c) shows the job mobility in all other industries. Grey bars denote NBER recession dates.

Figure B.5. Workers Age by Employment Status, 1996 – 2018



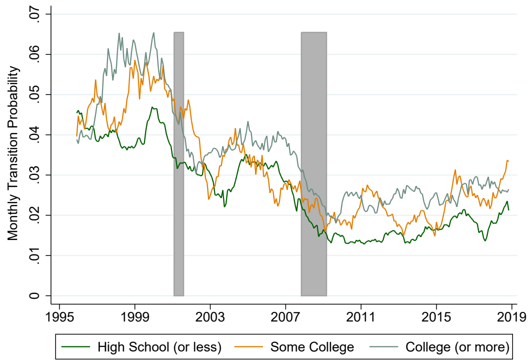
Notes: All Shares are constructed using yearly CPS data. Grey bars denote NBER recession dates.

Figure B.6. Ratio of IPT-FT to FT-FT Transition Probabilities by Age Group, 1996 – 2018

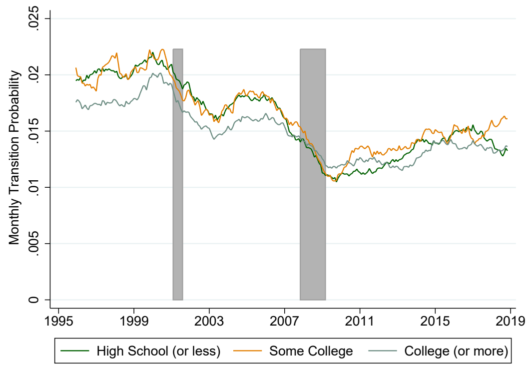


Notes: All Ratios are constructed using monthly CPS data. Grey bars denote NBER recession dates.

Figure B.7. Transition Probability by Job Transition Status and Education, 1996 – 2018



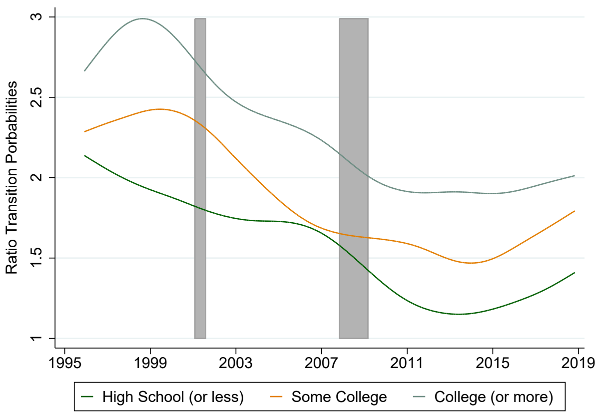
(a) IPT-FT



(b) FT-FT

Notes: All flows are constructed using monthly CPS data. I plot twelve-months moving averages of monthly data. Grey bars denote NBER recession dates.

Figure B.8. Ratio of IPT-FT to FT-FT Transition Probabilities Educational Group, 1996 – 2018



Notes: All Ratios are constructed using monthly CPS data. Grey bars denote NBER recession dates.

B.2 Data Appendix

In Table B.3 I provide the complete list of control variables used in the regressions in Section 3.3.5.

Table B.3. List of Control Variables

Industry controls	
Shares of workers employed in industry groups:	CPS
construction; manufacturing; transportation, communications, and other public utilities;	
wholesale and retail trade; services; finance, insurance, and real estate	
Import penetration China	AD
Industry controls	
Shares of workers employed in occupational groups:	CPS
abstract; routine; manual	
Worker controls	
Relative low to high educated workers: Ratio less than high school to at least high school	CPS
Shares of population in age groups 16-24; 25-34; 35-54; 55-65	CPS
Share of male population	CPS

Notes: AD: Autor and Dorn (2013); CPS: Current Population Survey.

B.3 Total Match Surplus

In this section, I derive the total surplus of a match between a worker with a preference for FT position matched to a PT firm in the model. Since the match surplus is given by $S_{IPT} = W_{IPT}(w_{IPT}(y), y) - B + \Pi_{IPT}(w_{IPT}(y), y)$, I substract the value of being unemployed, B, from both sides of the value function of an employed IPT workers, which results in

$$
\begin{aligned}
W_{IPT}(w_{IPT}(y), y) - B = w_{IPT}(y) - B + \frac{1}{1+r}& \\
\Big\{\delta B + (1-\delta)\Big[\sum_j \sum\nolimits_{y':P} \lambda_e \frac{v_j(y')}{V} W_j(w_j'(y', y), y')& \\
+ \sum_j \sum\nolimits_{y':B} \lambda_e \frac{v_j(y')}{V} W_{IPT}(w_{IPT}'(y, y'), y)& \\
+ \Big(1 - \sum_j \sum\nolimits_{y':CT} \lambda_e \frac{v_j(y)}{V}\Big) W_{IPT}(w_j(y), y)\Big]\Big\}&.
\end{aligned}
$$

After some rearrangement, this simplifies to

$$
\begin{aligned}
W_{IPT}(w_{IPT}(y), y) - B = w_{IPT}(y) - b + \frac{1-\delta}{1+r}\Big\{\sum_j \sum\nolimits_{y':P} \lambda_e \frac{v_j(y')}{V} S_{IPT}(y)& \\
+ \sum\nolimits_{y':B} \lambda_e \frac{v_{FT}(y')}{V} S_{FT}(y')& \\
+ \sum\nolimits_{y':B} \lambda_e \frac{v_{IPT}(y')}{V} S_{IPT}(y')& \\
+ \Big(1 - \sum_j \sum\nolimits_{y':CT} \lambda_e \frac{v_j(y)}{V}\Big)(W_{IPT}(w_j(y), y) - B)\Big\}&.
\end{aligned}
$$

Rewrite the firm surplus (Equation 3.6) as

$$
\begin{aligned}
\Pi_{IPT}(w_{IPT}(y), y) = f_{IPT}(y) - w_{IPT}(y) + \frac{1-\delta}{1+r}\Big\{& \\
\sum\nolimits_{y':B} \lambda_e \frac{v_{FT}(y')}{V} (S_{IPT}(y) - S_{FT}(y'))& \\
+ \sum\nolimits_{y':B} \lambda_e \frac{v_{IPT}(y')}{V} (S_{IPT}(y) - S_{IPT}(y'))& \\
+ \Big(1 - \sum_j \sum\nolimits_{y':CT} \lambda_e \frac{v_j(y)}{V}\Big) \Pi_{IPT}(w_{IPT}(y), y)\Big\}&.
\end{aligned}
$$

By combining the above derived results, for firms and workers surpluses, the total match surplus is

$$
\begin{aligned}
S_{IPT} &= W_{IPT}(w_{IPT}(y), y) - B + \Pi_{IPT}(w_{IPT}(y), y) \\
&= f_{IPT}(y) - w_{IPT}(y) + w_{IPT}(y) - b + \frac{1-\delta}{1+r}\Big\{ \\
&\textstyle\sum_{y':B} \lambda_e \frac{v_{FT}(y')}{V}(S_{IPT}(y) - S_{FT}(y')) \\
&+ \textstyle\sum_{y':B} \lambda_e \frac{v_{IPT}(y')}{V}(S_{IPT}(y) - S_{IPT}(y')) \\
&+ \Big(1 - \sum_j \textstyle\sum_{y':CT} \lambda_e \frac{v_j(y)}{V}\Big)\Pi_{IPT}(w_{IPT}(y), y) \\
&+ \sum_j \textstyle\sum_{y':P} \lambda_e \frac{v_j(y')}{V} S_{IPT}(y) \\
&+ \textstyle\sum_{y':B} \lambda_e \frac{v_{FT}(y')}{V} S_{FT}(y') \\
&+ \textstyle\sum_{y':B} \lambda_e \frac{v_{IPT}(y')}{V} S_{IPT}(y') \\
&+ \Big(1 - \sum_j \textstyle\sum_{y':CT} \lambda_e \frac{v_j(y)}{V}\Big)(W_{IPT}(w_j(y), y) - B)\Big\}.
\end{aligned}
$$

After some rearrangement, it follows that

$$
\begin{aligned}
S_{IPT} &= f_{IPT}(y) - b + \frac{1-\delta}{1+r}\Big\{ \sum_j \textstyle\sum_{y':P} \lambda_e \frac{v_j(y')}{V} S_{IPT}(y) \\
&+ \sum_j \textstyle\sum_{y':B} \lambda_e \frac{v_j(y')}{V} S_{IPT}(y) \\
&+ \Big(1 - \sum_j \textstyle\sum_{y':CT} \lambda_e \frac{v_j(y)}{V}\Big) \\
&(\Pi_{IPT}(w_{IPT}(y), y) + W_{IPT}(w_j(y), y) - B)\Big\}.
\end{aligned}
$$

The surplus can be simplified to

$$
\begin{aligned}
S_{IPT} &= f_{IPT}(y) - b + \frac{1-\delta}{1+r} S_{IPT} \\
&= \left(\frac{1+r}{r+\delta}\right)[f_{IPT}(y) - b].
\end{aligned}
$$

The derivations for S_{VPT} and S_{FT} follow analogously.

B.4 Value of a New Match

FT and PT firms' vacancy posting problems can be rewritten as

$$\begin{aligned}
&\max_{v_{FT}(y)} \Big\{ -c(v_{FT}(y)) + qv_{FT}(y)\Big(\frac{\lambda_u U_{FT}}{M}\max\{S_{FT}(y),0\} \\
&\quad + \sum_{y'} \frac{(1-\delta)\lambda_e n_{FT}(y')}{M}\max\{S_{FT}(y)-S_{FT}(y'),0\} \\
&\quad + \sum_{y'} \frac{(1-\delta)\lambda_e n_{IPT}(y')}{M}\max\{S_{FT}(y)-S_{IPT}(y'),0\}\Big)\Big\}, \\
&\max_{v_{PT}(y)} \Big\{ -c(v_{PT}(y)) + qv_{PT}(y)\Big(\frac{\lambda_u U_{PT}}{M}\max\{S_{VPT}(y),0\} && \text{(B.1)} \\
&\quad + \frac{\lambda_u U_{FT}}{M}\max\{S_{IPT}(y),0\} \\
&\quad + \sum_{y'} \frac{(1-\delta)\lambda_e n_{VPT}(y')}{M}\max\{S_{VPT}(y)-S_{VPT}(y'),0\} \\
&\quad + \frac{(1-\delta)\lambda_e n_{IPT}(y')}{M}\max\{S_{IPT}(y)-S_{IPT}(y'),0\}\Big)\Big\}. && \text{(B.2)}
\end{aligned}$$

For the expected value of a new match for a FT and PT firm, $J_{FT}(y)$ and $J_{PT}(y)$ respectively, it follows that

$$\begin{aligned}
J_{FT}(y) &= \frac{\lambda_u U_{FT}}{M}\max\{S_{FT}(y),0\} + \sum_{y'} \frac{(1-\delta)\lambda_e n_{FT}(y')}{M}\max\{\Pi_{FT}(w_{FT}(y,y'),y),0\} \\
&\quad + \sum_{y'} \frac{(1-\delta)\lambda_e n_{IPT}(y')}{M}\max\{\Pi_{FT}(w(y,y'),y),0\} \\
J_{PT}(y) &= \frac{\lambda_u U_{PT}}{M}\max\{S_{PT}(y),0\} + \frac{\lambda_u U_{FT}}{M}\max\{S_{IPT}(y),0\} \\
&\quad + \sum_{y'} \frac{(1-\delta)\lambda_e n_{VPT}(y')}{M}\max\{\Pi_{VPT}(w_{VPT}(y,y'),y),0\} \\
&\quad + \sum_{y'} \frac{(1-\delta)\lambda_e n_{IPT}(y')}{M}\max\{\Pi_{IPT}(w_{IPT}(y,y'),y),0\}.
\end{aligned}$$

With the result for the match surplus (Equation 3.13) it follows for FT firms:[1]

$$\begin{aligned}
J_{FT}(y_1) &= \frac{\lambda_u U_{FT}}{M}S_{FT}(y_1) + \frac{(1-\delta)\lambda_e n_{IPT}(y_1)}{M}(S_{FT}(y_1)-S_{IPT}(y_1)) \\
&\quad + \frac{(1-\delta)\lambda_e n_{IPT}(y_2)}{M}(S_{FT}(y_1)-S_{IPT}(y_2)),
\end{aligned}$$

[1] I assume that the match with an unemployed worker always exhibits a positive surplus

$$\begin{aligned}J_{FT}(y_2) = &\frac{\lambda_u U_{FT}}{M} S_{FT}(y_2) + \frac{(1-\delta)\lambda_e n_{FT}(y_1)}{M}(S_{FT}(y_2) - S_{FT}(y_1)) \\ &+ \frac{(1-\delta)\lambda_e n_{IPT}(y_1)}{M}(S_{FT}(y_2) - S_{IPT}(y_1)) \\ &+ \frac{(1-\delta)\lambda_e n_{IPT}(y_2)}{M}(S_{FT}(y_2) - S_{IPT}(y_2))\end{aligned}$$

And for PT firms:

$$\begin{aligned}J_{PT}(y_1) = &\frac{\lambda_u \left[U_{PT} + \delta N_{PT}\right]}{M} S_{PT}(y_1) + \frac{\lambda_u \left[U_{FT} + \delta N_{FT}\right]}{M} S_{IPT}(y_1), \\ J_{PT}(y_2) = &\frac{\lambda_u \left[U_{PT} + \delta N_{PT}\right]}{M} S_{PT}(y_2) + \frac{\lambda_u \left[U_{PT} + \delta N_{PT}\right]}{M} S_{IPT}(y_2) \\ &+ \frac{(1-\delta)\lambda_e n_{VPT}(y_1)}{M}(S_{VPT}(y_2) - S_{VPT}(y_1)) \\ &+ \frac{(1-\delta)\lambda_e n_{IPT}(y_1)}{M}(S_{IPT}(y_2) - S_{IPT}(y_1)).\end{aligned}$$

B.5 Employment and Unemployment Rates

The inflows into unemployment for workers with a preference for FT or PT jobs are given by

$$\begin{aligned}&\delta\left(1 - \sum_i \lambda_u \frac{v_{FT}(y_i) + v_{PT}(y_i)}{V}\right) \sum_i \left[n_{FT}(y_i) + n_{IPT}(y_i)\right] \\ &= \delta(1-\lambda_u) \sum_i \left[n_{FT}(y_i) + n_{IPT}(y_i)\right], \\ &\delta\left(1 - \sum_i \lambda_u \frac{v_{PT}(y_i)}{V}\right) \sum_i n_{VPT}(y_i) \\ &= \delta(1-\mu_{PT}\lambda_u) \sum_i n_{VPT}(y_i).\end{aligned}$$

The outflows from unemployment are given by

$$\begin{aligned}\left(\sum_i \lambda_u \frac{v_{FT}(y_i) + v_{PT}(y_i)}{V}\right) U_{FT}(y_i) &= \lambda_u U_{FT}, \\ \left(\sum_i \lambda_u \frac{v_{PT}(y_i)}{V}\right) U_{PT}(y_i) &= \mu_{PT}\lambda_u U_{PT}.\end{aligned}$$

By focusing on the steady state, employment and unemployment transitions for workers with a preference for FT and PT jobs are equal. With $P_{FT} = \sum_i \left[n_{FT}(y_i) + n_{IPT}(y_i)\right] + U_{FT}$ and $P_{PT} = \sum_i n_{VPT}(y_i) + U_{PT}$ it follows for the employment and unemployment rate for both worker types

$$\frac{N_{FT}}{P_{FT}} = \frac{\lambda_u}{\lambda_u + \delta(1-\lambda_u)}, \; \frac{N_{PT}}{P_{PT}} = \frac{\mu_{PT}\lambda_u}{\mu_{PT}\lambda_u + \delta(1-\mu_{PT}\lambda_u)}$$
$$\frac{U_{FT}}{P_{FT}} = \frac{\delta(1-\lambda_u)}{\lambda_u + \delta(1-\lambda_u)}, \; \frac{U_{PT}}{P_{PT}} = \frac{\delta(1-\mu_{PT}\lambda_u)}{\mu_{PT}\lambda_u + \delta(1-\mu_{PT}\lambda_u)}$$

From equalizing both unemployment and employment flows it follows that

$$\frac{u_{FT}}{P_{FT}} < \frac{u_{PT}}{P_{PT}}$$
$$\frac{\delta(1-\lambda_u)}{\lambda_u + \delta(1-\lambda_u)} < \frac{\delta(1-\mu_{PT}\lambda_u)}{\mu_{PT}\lambda_u + \delta(1-\mu_{PT}\lambda_u)}$$
$$\delta\mu_{PT}\lambda < \delta\lambda$$
$$\mu_{PT} < 1$$

Since $\mu_u = \frac{\sum_i v_{PT}(y_i)}{\sum_i v_{PT}(y_i) + \sum_i v_{FT}(y_i)} = \frac{V_{PT}}{V_{PT}+V_{FT}}$, $\mu_{PT} < 1$ holds if $V_{FT} > 0$. With $\frac{N_{FT}}{P_{FT}} = 1 - \frac{u_{FT}}{P_{FT}}$ and $\frac{N_{PT}}{P_{PT}} = 1 - \frac{u_{PT}}{P_{PT}}$ it directly follows that $\frac{N_{FT}}{P_{FT}} > \frac{N_{PT}}{P_{PT}}$ if $V_{FT} > 0$.

B.6 Match Surplus and Selective Hiring

The match surplus for a IPT worker/firm pair with selective hiring is given by

$$\begin{aligned}
&W_{IPT}(w_{IPT}(y), y) - B + \Pi_{IPT}(w_{IPT}(y), y) \\
&= f_{IPT}(y) - w_{IPT}(y) + w_{IPT}(y) - b + \frac{1-\delta}{1+r}\Big\{ \\
&\sum\nolimits_{y':B} \lambda_e(1-s)\frac{v_{FT}(y')}{V}(S_{IPT}(y) - S_{FT}(y')) \\
&+ \sum\nolimits_{y':B} \lambda_e \frac{v_{IPT}(y')}{V}(S_{IPT}(y) - S_{IPT}(y')) \\
&+ \Big(1 - \sum\nolimits_{y':CT} \lambda_e(1-s)\frac{v_{FT}(y)}{V} \\
&- \sum\nolimits_{y':CT} \lambda_e \frac{v_{IPT}(y)}{V}\Big)\Pi_{IPT}(w_{IPT}(y), y) \\
&+ \sum\nolimits_{y':P} \lambda_e(1-s)\frac{v_{FT}(y')}{V} S_{IPT}(y) + \sum\nolimits_{y':P} \lambda_e \frac{v_{IPT}(y')}{V} S_{IPT}(y) \\
&+ \sum\nolimits_{y':B} \lambda_e(1-s)\frac{v_{FT}(y')}{V} S_{FT}(y') + \sum\nolimits_{y':B} \lambda_e \frac{v_{IPT}(y')}{V} S_{IPT}(y') \\
&+ \Big(1 - \sum\nolimits_{y':CT} \lambda_e(1-s)\frac{v_{FT}(y)}{V} \\
&- \sum\nolimits_{y':CT} \lambda_e \frac{v_{IPT}(y)}{V}\Big)(W_{IPT}(w_j(y), y) - B)\Big\}.
\end{aligned}$$

After some rearrangement, it follows that

$$
\begin{aligned}
S_{IPT} = f_{IPT}(y) - b + \frac{1-\delta}{1+r}\Big\{ & \sum\nolimits_{y':P} \lambda_e (1-s)\frac{v_{FT}(y')}{V} S_{IPT}(y) \\
& + \sum\nolimits_{y':P} \lambda_e \frac{v_{IPT}(y')}{V} S_{IPT}(y) \\
& + \sum\nolimits_{y':B} \lambda_e (1-s)\frac{v_{FT}(y')}{V} S_{IPT}(y) \\
& + \sum\nolimits_{y':B} \lambda_e \frac{v_{IPT}(y')}{V} S_{IPT}(y) \\
& + \Big(1 - \sum\nolimits_{y':CT} \lambda_e (1-s)\frac{v_{FT}(y)}{V} \\
& - \sum\nolimits_{y':CT} \lambda_e \frac{v_{IPT}(y)}{V}\Big)(\Pi_{IPT}(w_{IPT}(y), y) + W_{IPT}(w_j(y), y) - B)\Big\}.
\end{aligned}
$$

The surplus can be simplified to

$$
\begin{aligned}
S_{IPT} &= f_{IPT}(y) - b + \frac{1-\delta}{1+r} S_{IPT} \\
&= \left(\frac{1+r}{r+\delta}\right)\left[f_{IPT}(y) - b\right].
\end{aligned}
$$

C Appendix to Chapter 4

C.1 Ideological Leanings in the District Courts

In Figures C.1–C.6 we provide evidence on the evolution of the average ideology score in each of the 90 U.S. district courts that have been active over our entire sample period from 1978 to 2011. While the ideology score did not experience a strong conservative shift in most district courts, there is some evidence of liberal (conservative) district courts becoming more conservative (liberal) over time. These slight tendencies towards the middle motivate us to include the lagged dependent variable in our regressions for district court rulings to account for mean-reverting dynamics which may also be present in rulings.

Figure C.1. Average Ideology Score in the District Courts (1/6)

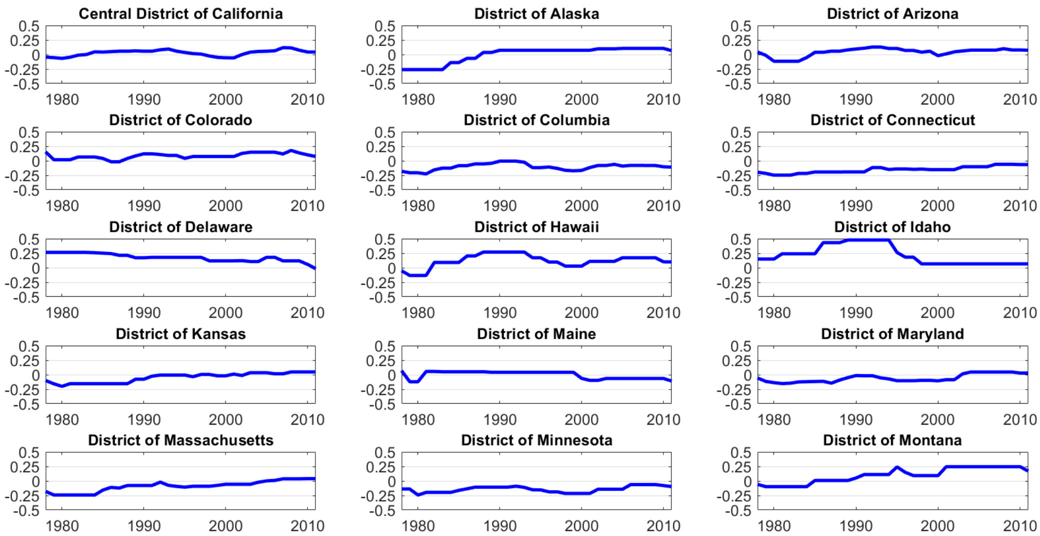


Figure C.2. Average Ideology Score in the District Courts (2/6)

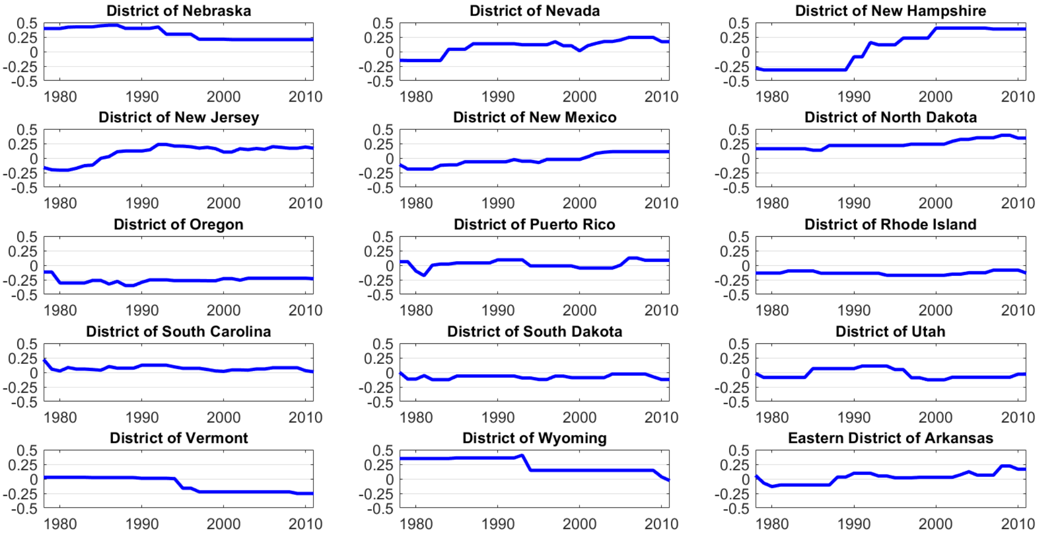


Figure C.3. Average Ideology Score in the District Courts (3/6)

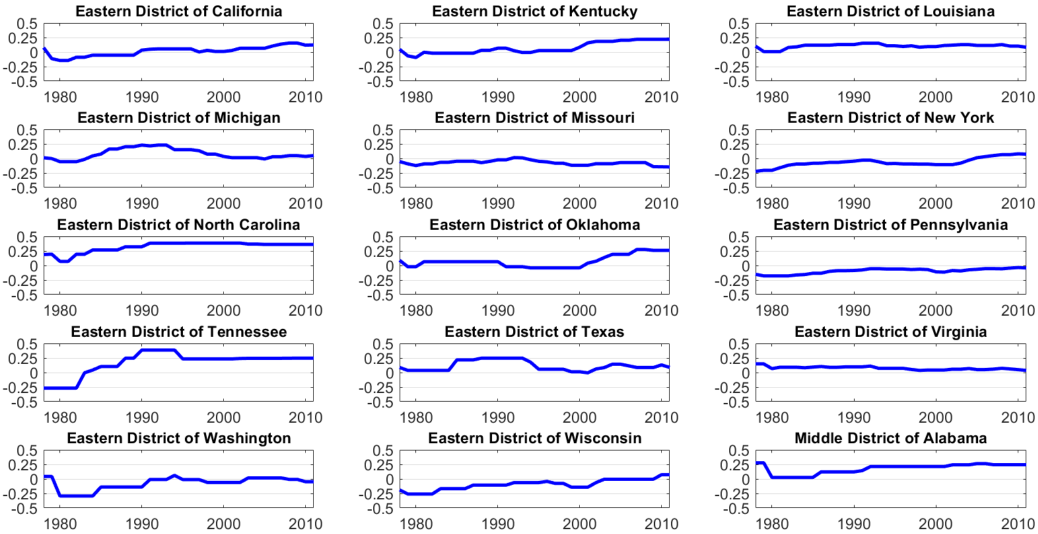


Figure C.4. Average Ideology Score in the District Courts (4/6)

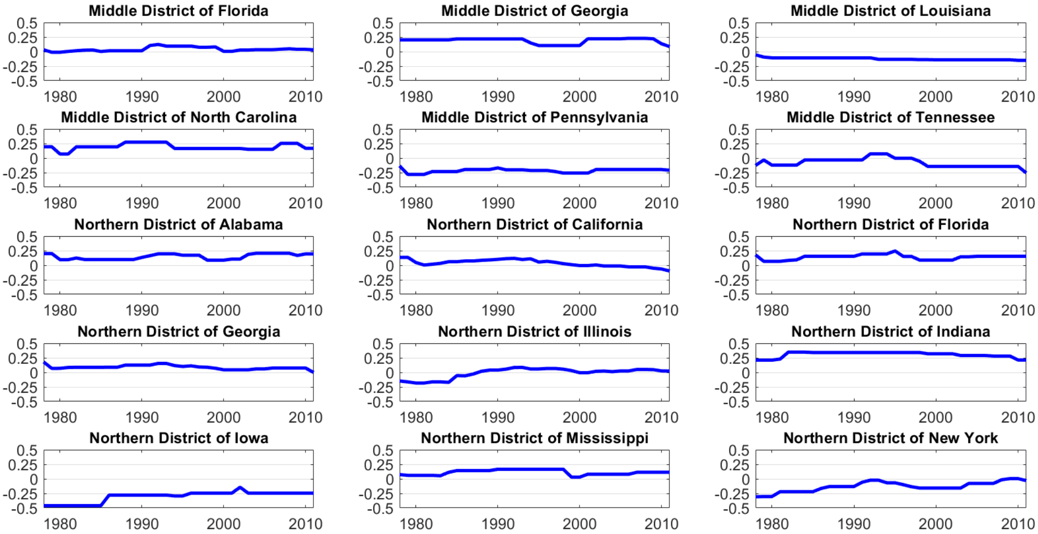


Figure C.5. Average Ideology Score in the District Courts (5/6)

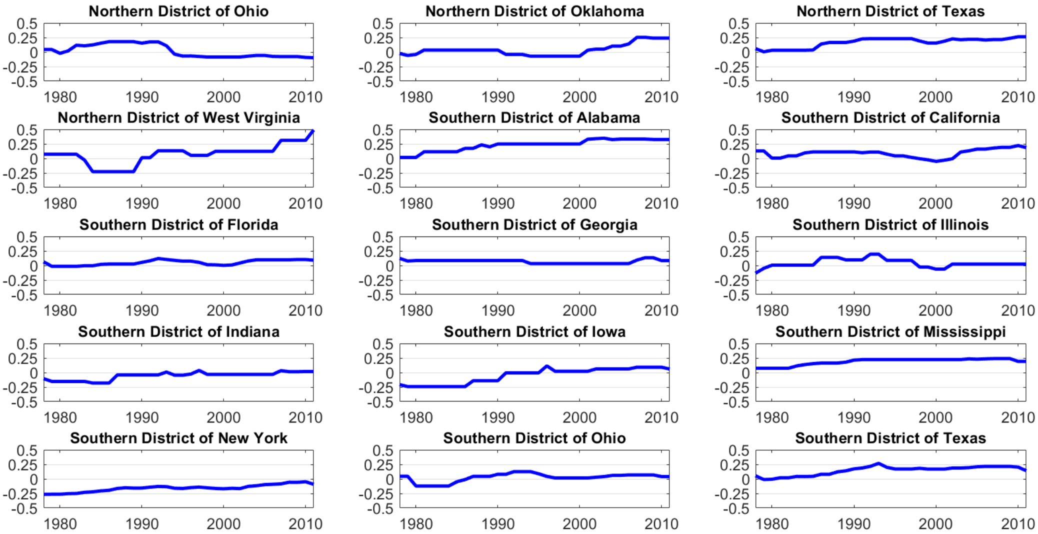
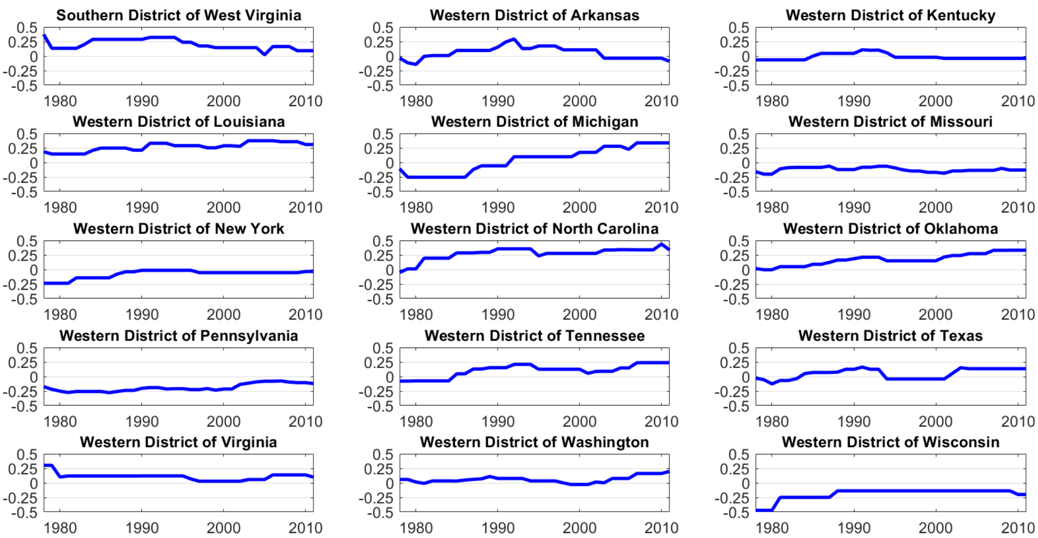


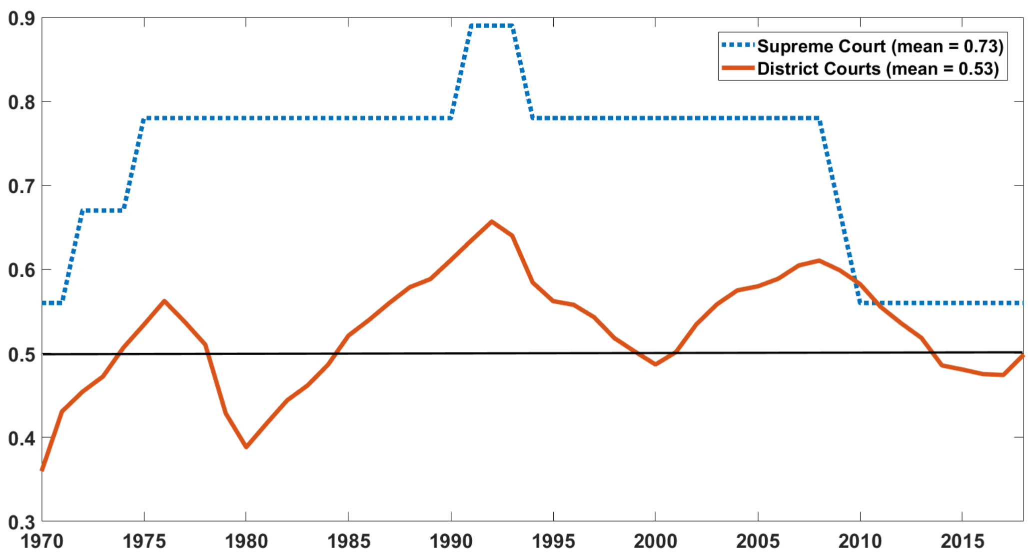
Figure C.6. Average Ideology Score in the District Courts (6/6)



C.2 Share of Judges Appointed by a Republican President

In this section we compare the share of district court judges appointed by Republican presidents to the share of Supreme Court justices appointed by Republican presidents. As depicted in Figure C.7, five of the nine Supreme Court Justices serving in 1970 have been appointed by a Republican president. This ratio increased to eight out of nine justices in the early 1990s and only reverted back in 2010. In contrast, the share of district court judges appointed by a Republican president has remained close to 50% over the entire time period. Thus, it is unlikely that the relative increase in the share of conservative rulings is driven by increasingly conservative district court judges. Furthermore, effects of changes in the national composition of district court judges are absorbed in the time fixed effects in our regressions.

Figure C.7. Share of Justices and Judges Appointed by a Republican President



Note: This graph depicts the share of Supreme Court justices and the share of district court judges appointed by a Republican president. The black line indicates parity between the number of justices and judges appointed by a Republican president and the number of justices and judges appointed by a Democratic president.

We additionally provide evidence on the evolution of the share of district court judges that were appointed by a Republican president in each district court in Figures C.8–C.13. The majority of the district courts did not experience a strong conservative shift between 1978 and 2011. However, as there is some evidence that at district courts where many judges were appointed by a Republican (Democratic) president the share of Republican (Democratic) appointees declines over time, we include the share of district court judges appointed by a Republican president as a control variable in our regressions.

Figure C.8. Share of District Court Judges Appointed by a Republican President (1/6)

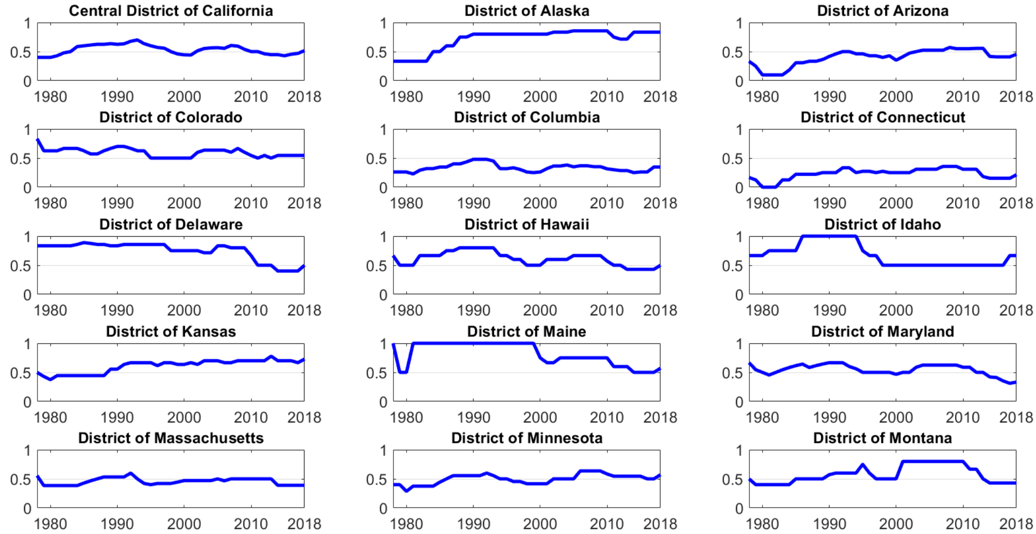


Figure C.9. Share of District Court Judges Appointed by a Republican President (2/6)

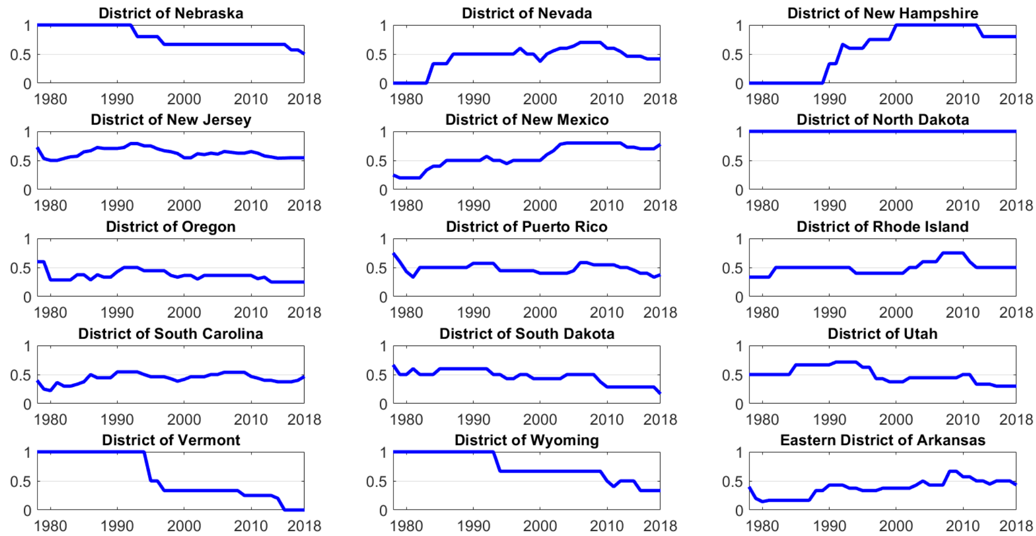


Figure C.10. Share of District Court Judges Appointed by a Republican President (3/6)

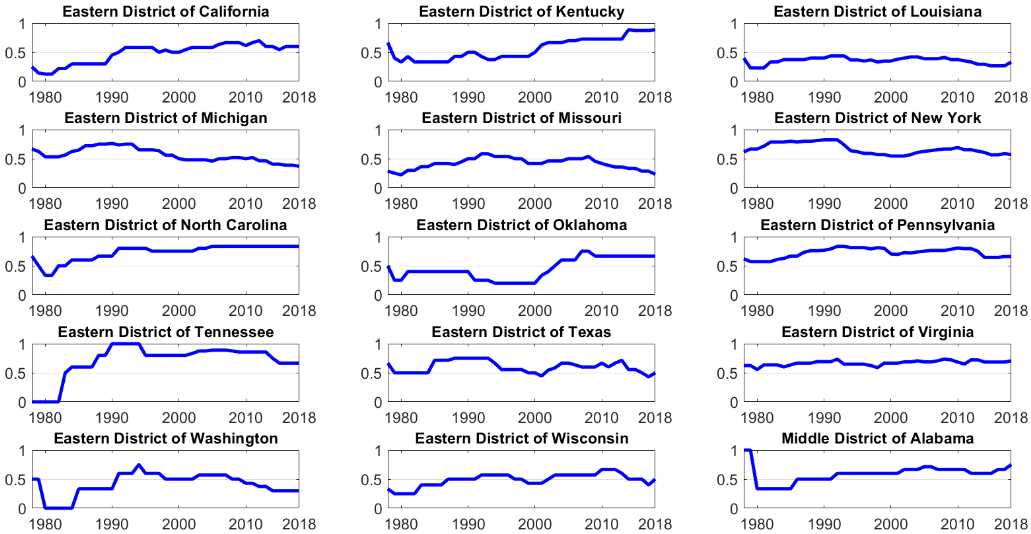


Figure C.11. Share of District Court Judges Appointed by a Republican President (4/6)

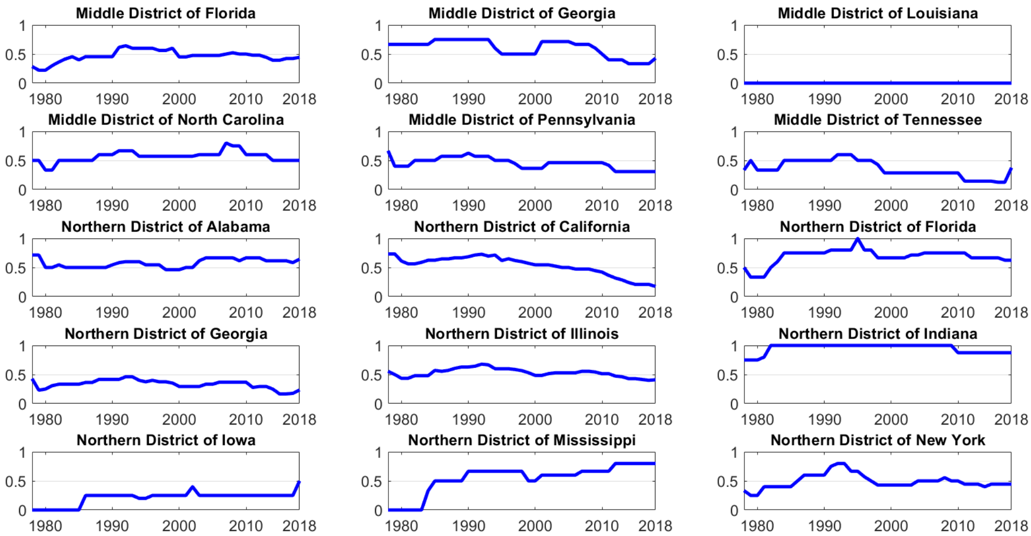


Figure C.12. Share of District Court Judges Appointed by a Republican President (5/6)

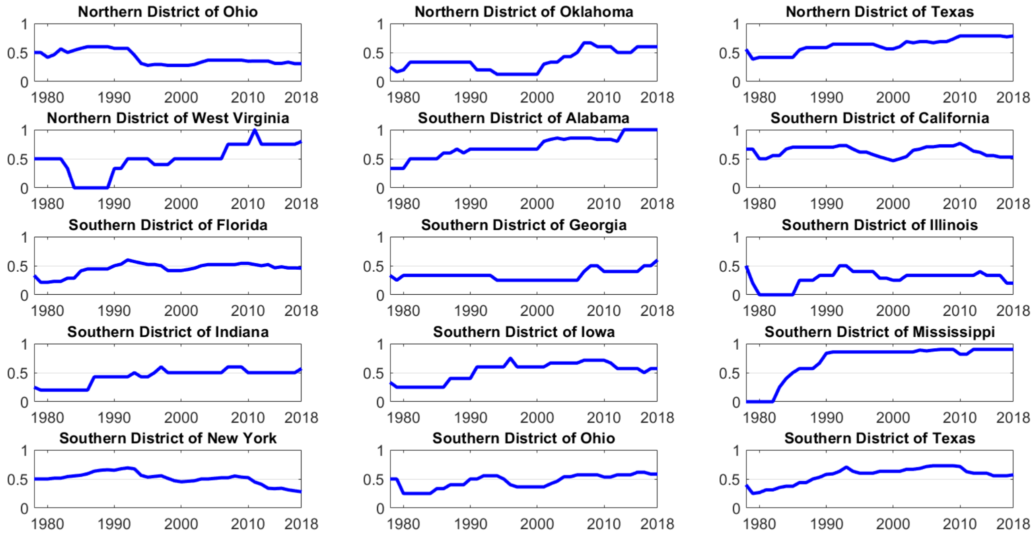
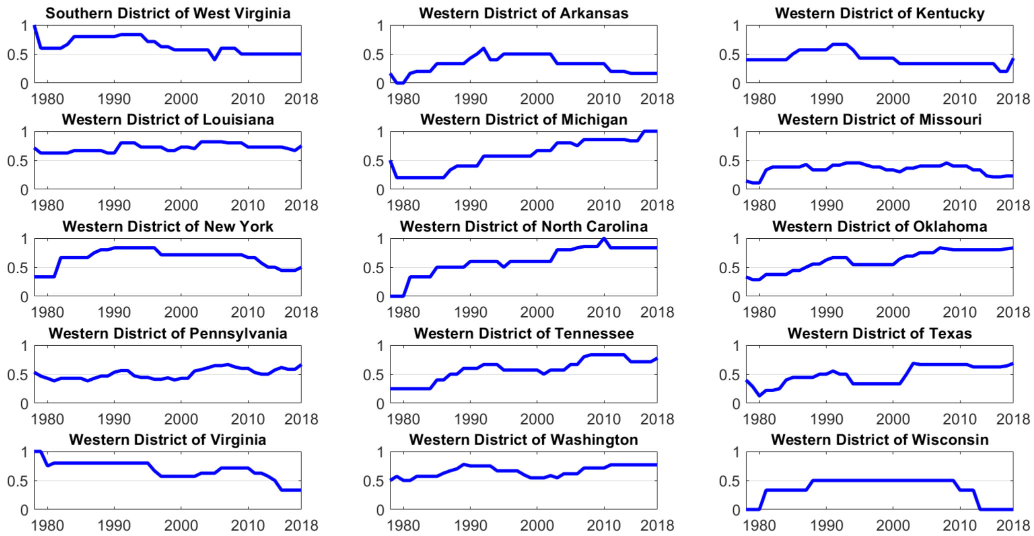


Figure C.13. Share of District Court Judges Appointed by a Republican President (6/6)



C.3 Further Rulings Regressions

In Table C.1 we present the results for several robustness checks. In Column (1), we control for local labor market conditions by including the unemployment rate and the real state GDP growth rate. This evaluation is motivated by the evidence that court rulings can be affected by economic conditions, see Section 4.2. In Column (2), we use a moving average over a four year window of our measure of Supreme Court ideology sci_t, taking into account the possibility that district court judges orientate themselves partly on past Supreme Court ideology. In Column (3), we include four (instead of one) lags of the dependent variable, allowing us to capture more general mean-reverting tendencies in district court rulings. Finally, in Column (4), we weigh rulings by the number of rulings per state population which reduces the importance of observations where unusually few rulings are published. In all of these specifications the coefficient on the interaction term between Supreme Court ideology and district court ideology remains negative and statistically significant.

Table C.1. Regression Results for District Court Rulings – Robustness Checks

	(1)	(2)	(3)	(4)
Supreme Court ideology	-2.0298		-2.0738	-1.7567
$\times$ district court ideology	(0.7114)		(0.7155)	(0.7227)
	p=0.0044		*p=0.0038*	*p=0.0152*
Supreme Court ideology (MA)		-1.7085		
$\times$ district court ideology		(0.9320)		
		p=0.0670		
Observations	1499	1499	1499	1499
R^2	0.2631	0.2592	0.2734	0.2748
Lagged dependent variable	yes	yes	yes	yes
Additional lags	no	no	yes	no
Weights	no	no	no	yes
State demographics	yes	yes	yes	yes
Court, judge, and case characteristics	yes	yes	yes	yes
State gov. and leg. controls	yes	yes	yes	yes
State GDP and unemployment	yes	no	no	no
Year fixed effects	yes	yes	yes	yes
State fixed effects	yes	yes	yes	yes

Note: The standard errors are reported in parantheses. The p-values are reported below the standerd errors. Supreme Court ideology (MA) = $1/4 \cdot \sum_{\tau=0}^{3} sci_{t-\tau}$.

C.4 Further Labor Market Regressions

In this section we present regressions for additional labor market outcomes and alternative specifications for the regressions in Section 4.4.

C.4.1 Additional Outcome Variables

First, we run the regression in Equation (4.6) for additional industry groups and for additional inequality measures. Table C.2 shows results for further industry groups. We find that conservative court rulings increase employment in financial industries disproportionately, while there is no discernible change in the trade and transportation employment shares. Table C.3 shows results for additional inequality measures, which support our findings of increasing inequality in response to rising judicial conservatism documented in Section 4.4.

Table C.2. Regression Results for Industry Employment Shares – Additional Industry Groups

	(1)	(2)	(3)
Dependent variable	Trade emp. share	Transport emp. share	Finance emp. share
Supreme Court ideology sci_t	0.0207	0.0206	−0.0287
× district court ideology dci_s	(0.0220)	(0.0132)	(0.0117)
	p= 0.3477	*p= 0.1177*	*p= 0.0148*
Observations	1499	1499	1499
R^2	0.5962	0.6122	0.7606
Industry and occupation controls	no	no	no
State policy controls	yes	yes	yes
State gov. and leg. controls	yes	yes	yes
Year fixed effects	yes	yes	yes
State fixed effects	yes	yes	yes

Note: The standard errors are reported in parantheses. The p-values are reported below the standard errors.

C.4.2 Alternative Specifications

Second, we present the results of several robustness checks. For simplicity, we concentrate on five dependent variables which represent our main results that conservative court rulings

Table C.3. Regression Results for Inequality – Additional Percentiles

	(1)	(2)	(3)
Dependent variable	80/20 percentiles	80/50 percentiles	50/20 percentiles
Supreme Court ideology sci_t	-0.2235	-0.1157	-0.1078
$\times$ district court ideology dci_s	(0.1037)	(0.0584)	(0.0807)
	p= 0.0313	*p= 0.0476*	*p= 0.1816*
Observations	1499	1499	1499
R^2	0.8427	0.8077	0.7182
Industry and occupation controls	yes	yes	yes
State policy controls	yes	yes	yes
State gov. and leg. controls	yes	yes	yes
Year fixed effects	yes	yes	yes
State fixed effects	yes	yes	yes

Note: The standard errors are reported in parantheses. The p-values are reported below the standard errors.

promote labor market fluidity but also contribute to wage stagnation, job market polarization, deunionization, and rising inequality. Specifically, we show results for the unemployment rate, the average hourly wage rate, the employment share in routine occupations, the union coverage rate, and the 90/10 income ratio.

In Table C.4, we additionally control for state demographics, which are also included in the regressions for district court rulings. Results are similar to the baseline case presented in Section 4.4.

In Tables C.5–C.7 we leave out sets of control variables one after another. These exercises serve two purposes. First, they reveal whether our results rely on specific control variables. Second, they are informative about endogenous responses of the control variables to changing Supreme Court ideology and their effects on our variables of interest. These indirect effects allow for a more complete picture of the effects of changing Supreme Court ideology but are not part of the direct effects of ideological leanings in court rulings which we are primarily interested in.

In Table C.5, we leave out control variables for state politics. This has no effect on the direction or the significance of the effects but changes the size of some coefficients visibly. For example, the effect on wage is strengthened, suggesting that increasing Supreme Court conservatism induces changes in state governments and legislatures which further weaken workers' bargaining power. In Table C.6, we leave out control variables for state-specific policies. The effects on the results are negligible. Finally, we refrain from controlling for the state's industry-occupation composition in Table C.7. By construction, the specification for the routine employment share is unchanged because it did not control for the industry-occupation composition in the first place. Most of the results are barely affected, only for the log hourly wage rate there seem to be some counteracting composition effects which weaken the precision of the estimate.

In Tables C.8 to C.13, we take into account additional interaction terms between both district court ideology and an alternative aggregate time-variant variable and between Supreme Court ideology and an alternative state-specific time-invariant variable. For example, we present results for a specification that includes an interaction term between overall import penetration from China and district court ideology i in addition to the main interaction term between Supreme Court ideology and district court ideology. Unsurprisingly, and in line with the literature on import competition from China (cf. Autor et al., 2013), this interaction term has a positive and significant effect on the unemployment rate, see Table C.8. Overall, despite the inclusion of additional interaction terms, our main interaction term remains highly statistically significant and quantitatively close to the results in the main text in all of the regressions. Providing a clear indication that our results are actually driven by the proposed interaction term between Supreme Court ideology and district court ideology and not by some other superimposing trend.

In Table C.14, we additionally control for pre-sample trends by including state-level income growth for the time period between 1950 and 1969.[1] Both the size of the effect of our interaction term and the statistical significance are nearly unchanged by the inclusion of this additional control variable, indicating that our results are not driven by pre-sample trends.

[1] 1950 is chosen as the starting date as 1949 is the first year for which data on state-level income for all states is available from the CPS. 1969 is chosen as the end date as this marks the year in which Supreme Court ideology began to shift towards the conservative end of the ideological spectrum, see Figure 4.1.

Table C.4. Regression Results – Controlling for State Demographics

	(1)	(2)	(3)	(4)	(5)
Dependent variable	Unemployment rate	Avg. hourly wage rate	Routine emp. share	Union coverage	90/10 percentiles
Supreme Court ideology sci_t	0.0706	0.1283	0.0706	0.1095	-0.4061
$\times$ district court ideology dci_s	(0.0209)	(0.0679)	(0.0251)	(0.0256)	(0.1604)
	p= 0.0008	*p= 0.0590*	*p= 0.0049*	*p= 0.0000*	*p= 0.0115*
Observations	1499	1499	1499	1499	1499
R^2	0.7617	0.9940	0.8335	0.9705	0.8266
Industry and occupation controls	yes	yes	no	yes	yes
State policy controls	yes	yes	yes	yes	yes
State gov. and leg. controls	yes	yes	yes	yes	yes
State demographics	yes	yes	yes	yes	yes
Year fixed effects	yes	yes	yes	yes	yes
State fixed effects	yes	yes	yes	yes	yes

Note: The standard errors are reported in parantheses. The p-values are reported below the standard errors.

Table C.5. Regression Results – Not Controlling for State Politics

	(1)	(2)	(3)	(4)	(5)
Dependent variable	Unemployment rate	Avg. hourly wage rate	Routine emp. share	Union coverage	90/10 percentiles
Supreme Court ideology sci_t	0.0736	0.2083	0.0659	0.1420	-0.3412
$\times$ district court ideology dci_s	(0.0208)	(0.0719)	(0.0249)	(0.0269)	(0.1589)
	p= 0.0004	*p= 0.0038*	*p= 0.0084*	*p= 0.0000*	*p= 0.0320*
Observations	1499	1499	1499	1499	1499
R^2	0.7535	0.9930	0.8262	0.9658	0.8217
Industry and occupation controls	yes	yes	no	yes	yes
State policy controls	yes	yes	yes	yes	yes
State gov. and leg. controls	no	no	no	no	no
Year fixed effects	yes	yes	yes	yes	yes
State fixed effects	yes	yes	yes	yes	yes

Note: The standard errors are reported in parantheses. The p-values are reported below the standard errors.

Table C.6. Regression Results – Not Controlling for State Policies

	(1)	(2)	(3)	(4)	(5)
Dependent variable	Unemployment rate	Avg. hourly wage rate	Routine emp. share	Union coverage	90/10 percentiles
Supreme Court ideology sci_t	0.0824	0.1412	0.1151	0.1447	-0.4649
$\times$ district court ideology dci_s	(0.0198)	(0.0663)	(0.0237)	(0.0255)	(0.1494)
	p= 0.0000	*p= 0.0333*	*p= 0.0000*	*p= 0.0000*	*p= 0.0019*
Observations	1499	1499	1499	1499	1499
R^2	0.7453	0.9932	0.8202	0.9650	0.8208
Industry and occupation controls	yes	yes	no	yes	yes
State policy controls	no	no	no	no	no
State gov. and leg. controls	yes	yes	yes	yes	yes
Year fixed effects	yes	yes	yes	yes	yes
State fixed effects	yes	yes	yes	yes	yes

Note: The standard errors are reported in parantheses. The p-values are reported below the standard errors.

Table C.7. Regression Results – Not Controlling for the Industry-Occupation Composition

	(1)	(2)	(3)	(4)	(5)
Dependent variable	Unemployment rate	Avg. hourly wage rate	Routine emp. share	Union coverage	90/10 percentiles
Supreme Court ideology sci_t	0.0658	0.0927	0.0633	0.1405	-0.5037
$\times$ district court ideology dci_s	(0.0209)	(0.0726)	(0.0250)	(0.0270)	0.1637
	p= 0.0017	*p= 0.2017*	*p= 0.0116*	*p= 0.0000*	*p= 0.0021*
Observations	1499	1499	1499	1499	1499
R^2	0.7430	0.9927	0.8267	0.9647	0.8057
Industry and occupation controls	no	no	no	no	no
State policy controls	yes	yes	yes	yes	yes
State gov. and leg. controls	yes	yes	yes	yes	yes
Year fixed effects	yes	yes	yes	yes	yes
State fixed effects	yes	yes	yes	yes	yes

Note: The standard errors are reported in parantheses. The p-values are reported below the standard errors.

Table C.8. Regression Results Unemployment Rate – Alternative Time-Variant Variable

	(1)	(2)	(3)
Alternative time-variant variable	Party of president	Capital price	Import China
Supreme Court ideology sci_t	0.0668	0.0490	0.0542
$\times$ district court ideology dci_s	(0.0208)	(0.0229)	(0.0218)
	p= 0.0014	*p= 0.0322*	*p= 0.0132*
Alternative time-variant variable	0.0104	0.0415	0.0370
$\times$ district court ideology dci_s	(0.0054)	(0.0185)	(0.0155)
	p= 0.0542	*p= 0.0254*	*p= 0.0174*
Observations	1499	1499	1499
R^2	0.7567	0.7570	0.7571
Industry and occupation controls	yes	yes	yes
State policy controls	yes	yes	yes
State gov. and leg. controls	yes	yes	yes
Year fixed effects	yes	yes	yes
State fixed effects	yes	yes	yes

Note: The standard errors are reported in parantheses. The p-values are reported below the standard errors.

Table C.9. Regression Results Unemployment Rate – Alternative Time-Invariant Variable

	(1)	(2)	(3)
Alternative time-invariant variable	Blue state	Routine share	Manufacturing share
Supreme Court ideology sci_t	0.0579	0.0580	0.0579
$\times$ district court ideology dci_s	(0.0226)	(0.0209)	(0.0207)
	p= 0.0105	*p= 0.0056*	*p= 0.0052*
Supreme Court ideology sci_t	0.0495	0.0429	0.0084
$\times$ Alternative time-invariant variable	(0.0350)	(0.0109)	(0.0016)
	p= 0.1577	*p= 0.0001*	*p= 0.0000*
Observations	1499	1499	1499
R^2	0.7564	0.7588	0.7608
Industry and occupation controls	yes	yes	yes
State policy controls	yes	yes	yes
State gov. and leg. controls	yes	yes	yes
Year fixed effects	yes	yes	yes
State fixed effects	yes	yes	yes

Note: The standard errors are reported in parantheses. The p-values are reported below the standard errors.

Table C.10. Regression Results Unemployment Rate – Alternative Interaction Terms

	(1)	(2)	(3)
Alternative interaction term	Party of president × Blue state	Capital price × Routine share	Import China × Manufacturing share
Supreme Court ideology sci_t	0.0635	0.0707	0.0723
× district court ideology dci_s	(0.0205)	(0.0208)	(0.0208)
	p= 0.0020	*p= 0.0007*	*p= 0.0005*
Alternative interaction term	0.0515	0.0050	0.0023
	(0.0077)	(0.0092)	(0.0011)
	p= 0.0000	*p= 0.5860*	*p= 0.0005*
Observations	1499	1499	1499
R^2	0.7638	0.7561	0.7568
Industry and occupation controls	yes	yes	yes
State policy controls	yes	yes	yes
State gov. and leg. controls	yes	yes	yes
Year fixed effects	yes	yes	yes
State fixed effects	yes	yes	yes

Note: The standard errors are reported in parantheses. The p-values are reported below the standard errors.

Table C.11. Regression Results 90/10 Percentiles – Alternative Time-Variant Variable

	(1)	(2)	(3)
Alternative time-variant variable	Party of president	Capital price	Import China
Supreme Court ideology sci_t	-0.3910	-0.2806	-0.3387
$\times$ district court ideology dci_s	(0.1598)	(0.1754)	(0.1677)
	p= 0.0145	*p= 0.1100*	*p= 0.0436*
Alternative time-variant variable	0.0654	-0.1672	-0.0649
$\times$ district court ideology dci_s	(0.0415)	(0.1423)	(0.1192)
	p= 0.1158	*p= 0.2403*	*p= 0.5862*
Observations	1499	1499	1499
R^2	0.8231	0.8230	0.8228
Industry and occupation controls	yes	yes	yes
State policy controls	yes	yes	yes
State gov. and leg. controls	yes	yes	yes
Year fixed effects	yes	yes	yes
State fixed effects	yes	yes	yes

Note: The standard errors are reported in parantheses. The p-values are reported below the standard errors.

Table C.12. Regression Results 90/10 Percentiles – Alternative Time-Invariant Variable

	(1)	(2)	(3)
Alternative time-invariant variable	Blue state	Routine share	Manufacturing share
Supreme Court ideology sci_t	-0.3001	-0.3075	-0.3507
$\times$ district court ideology dci_s	(0.1733)	(0.1607)	(0.1603)
	p= 0.0836	*p= 0.0560*	*p= 0.0288*
Supreme Court ideology sci_t	-0.2630	-0.2053	-0.0111
$\times$ Alternative time-invariant variable	(0.2683)	(0.0837)	(0.0124)
	p= 0.3271	*p= 0.0143*	*p= 0.3726*
Observations	1499	1499	1499
R^2	0.8229	0.8235	0.8229
Industry and occupation controls	yes	yes	yes
State policy controls	yes	yes	yes
State gov. and leg. controls	yes	yes	yes
Year fixed effects	yes	yes	yes
State fixed effects	yes	yes	yes

Note: The standard errors are reported in parantheses. The p-values are reported below the standard errors.

Table C.13. Regression Results 90/10 Percentiles – Alternative Interaction Terms

	(1)	(2)	(3)
Alternative interaction term	Party of president × Blue state	Capital price × Routine share	Import China × Manufacturing share
Supreme Court ideology sci_t	-0.4065	-0.3740	-0.3775
× district court ideology dci_s	(0.1581)	(0.1588)	(0.1592)
	p= 0.0103	*p= 0.0187*	*p= 0.0179*
Alternative interaction term	0.2847	-0.2001	-0.0128
	(0.0591)	(0.0705)	(0.0085)
	p= 0.0000	*p= 0.0046*	*p= 0.1329*
Observations	1499	1499	1499
R^2	0.8257	0.8238	0.8231
Industry and occupation controls	yes	yes	yes
State policy controls	yes	yes	yes
State gov. and leg. controls	yes	yes	yes
Year fixed effects	yes	yes	yes
State fixed effects	yes	yes	yes

Note: The standard errors are reported in parantheses. The p-values are reported below the standard errors.

Table C.14. Regression Results – Controlling for Pre-Sample Income Growth

	(1)	(2)	(3)	(4)	(5)
Dependent variable	Unemployment rate	Avg. hourly wage rate	Routine emp. share	Union coverage	90/10 percentiles
Supreme Court ideology sci_t	0.0667	0.1299	0.0672	0.1089	-0.3554
$\times$ district court ideology dci_s	(0.0208)	(0.0693)	(0.0251)	(0.0258)	(0.1597)
	p= 0.0014	*p= 0.0611*	*p= 0.0075*	*p= 0.0000*	*p= 0.0262*
Observations	1499	1499	1499	1499	1499
R^2	0.7570	0.9936	0.8272	0.9691	0.8229
Industry and occupation controls	yes	yes	yes	yes	yes
State policy controls	yes	yes	yes	yes	yes
State gov. and leg. controls	yes	yes	yes	yes	yes
Pre-sample trend	yes	yes	yes	yes	yes
Year fixed effects	yes	yes	yes	yes	yes
State fixed effects	yes	yes	yes	yes	yes

Note: The standard errors are reported in parantheses. The p-values are reported below the standard errors.

C.5 Data Appendix

In Tables C.15, C.16, and C.17 we provide a complete list of dependent variables and a complete list of control variables that were used in our regressions. All regressions include state and year fixed effects. GDP growth by state is calculated using data from the Bureau of Economic Analysis. The term publishing judge refers to the judge publishing the opinion in the Federal Supplement. Concerning the state legislature controls, Nebraska constitutes an exception in the sense that it is both unicameral and officially non-partisan. We decide to use the de facto majority in the Nebraska legislature for both the state house and state senate variable. However, as the state legislature in Nebraska has featured a de facto Republican majority in all years of our sample, independent of how we handle Nebraska, effects of the state legislature will be absorbed in the state fixed effect.

Table C.15. Dependent Variables

Dependent variable in Section 3 and Appendix C	
Average ideology score (1: conservative, -1: liberal) of rulings in Economic Regulation and/or Labor Cases in federal district courts by state and year	CM
Dependent variables in Section 4 and Appendix D.2	
Unemployment rate (number unemployed divided by labor force)	CPS
Job-finding rate (inverse of average duration of unemployment in weeks)	CPS
Employment rate (number employed divided by adult population)	CPS
Avg. hourly wage rate (log of the wage rate)	CPS
Vol. PT share (log of number voluntary part-time employed divided by all employed)	CPS
PT/FT wage rate (log of voluntary part-time wages divided by full-time wages)	CPS
Employment share in construction industries	CPS
Employment share in manufacturing industries	CPS
Employment share in service industries	CPS
Employment share in abstract-intensive occupations	CPS + AD
Employment share in routine-intensive occupations	CPS + AD
Employment share in manual task intensive occupations	CPS + AD
90/10 percentiles (log of 90th percentile family income divided by 10th percentile)	CPS
90/50 percentiles (log of 90th percentile family income divided by 50th percentile)	CPS
50/10 percentiles (log of 50th percentile family income divided by 10th percentile)	CPS
Dependent variables in Appendix D.1	
Employment share in wholesale and retail trade industries	CPS
Employment share in transportation, communications, and other public utilities industries	CPS
Employment share in finance, insurance, and real estate industries	CPS
80/20 percentiles (log of 80th percentile family income divided by 20th percentile)	CPS
80/50 percentiles (log of 80th percentile family income divided by 50 percentile)	CPS
50/20 percentiles (log of 50th percentile family income divided by 20th percentile)	CPS

Note: AD: Autor and Dorn (2013); CM: Carp and Manning (2016); CPS: Current Population Survey.

Table C.16. Independent Variables I

Regressor of interest	
Median ideology score of Supreme Court justices by year × pre-sample average ideology score of district court judges by state	Boyd + Bailey
Court, Judge, and Case Characteristics	
Share of judges appointed by a Republican president	CM+FJC
Average ideology score at the responsible court of appeals	CM+FJC
Share of cases in each case type category in the U.S. District Court Database (union v. company; member v. union; employee v. employer; commercial regulation; environmental protection local/state economic; labor dispute – govt v. union/employer; rent control; excess profits)	CM
Average age of district court judges	FJC
Share of white district court judges	FJC
Share of male district court judges	FJC
Share of publishing judges with Republican Party affiliation	CM
Share of publishing judges with Democrat Party affiliation	CM
Share of white publishing judges	CM
Share of male publishing judges	CM
Shares of publishing judges appointed by each president	CM
Experience of publishing judges (years of service at current court, shares)	CM
State demographics	
Total adult state population	CPS
Share of population living in a central city (urban density)	CPS
Share of population living in a city (urban density)	CPS
Share of black population (ethnic composition)	CPS
Share of white population (ethnic composition)	CPS
Shares of population in age groups 16-24; 25-44; 45-54; >55	CPS
Industry-occupation controls	
Shares of workers employed in industry groups: construction; manufacturing; transportation communications, and other public utilities; wholesale and retail trade; services; finance, insurance, and real estate	CPS
Shares of workers employed in occupational groups: abstract; manual; routine	CPS + AD

Note: ADS: AD: Autor and Dorn (2013); Autor et al. (2006a); Bailey: Bailey (2013); CM: Carp and Manning (2016); CPS: Current Population Survey; FJC: Federal Judicial Center: Biographical Directory of Article III Federal Judges.

Table C.17. Independent Variables II

State policy controls	
Minimum wage rate	FRED
Total federal intergovernmental revenue	SLGFD
Total tax burden	TF
Public policy exception to employment at-will	ADS
Implied contract exception to employment at-will	ADS
Good faith exception to employment at-will	ADS
State gov. and leg. controls	
State senate majority party	NCLS
(1: Rep., -1: Dem., 0: other/indep./no majority)	
State house majority party	NCLS
(1: Rep., -1: Dem., 0: other/indep./no majority)	
Political party of the governor	NCLS
(1: Rep., -1: Dem., 0: other/indep./no majority)	
Additional control variables in robustness checks	
State unemployment rate	FRED
Growth rate of real state GDP	BEA
Voting share for John McCain in 2008 presidential election	FEC
× Republican president	

Note: ADS: AD: Autor and Dorn (2013); Autor et al. (2006a); Bailey: Bailey (2013); BEA: Bureau of Economic Analysis; FEC: Federal Election Commission; FRED: Federal Reserve Economic Data; NCLS: National Conference of State Legislatures; SLGFD: State and Local Government Finance Dataset; TF: Tax Foundation.

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Ausbildung

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Forschungsprojekte und Veröffentlichungen

Die Polarisierung des Arbeitsmarktes und die Bedeutung von Gewerkschaften, *mit Tobias Föll, Theresa Markefke und Rebekka Rehm*
Kölner Impulse zur Wirtschaftspolitik, Ausgabe 05/2019

Deflation und Konsumstau: Mikroökonomische Evidenz , *mit Henning Klodt*
Credit and Capital Markets – Kredit und Kapital, 2014, 47(3), 397-414

A Joint Theory of Polarization and Deunionization, *mit Tobias Föll (Revise and Resubmit, Review of Economic Dynamics)*

The Role of Job-to-Job Transitions for Involuntary Part-Time Employment

Out-Lawed: Estimating the Effects of Ideological Leanings of U.S. Supreme Court Justices on Labor Market Prospects, *mit Christian Bredemeier und Tobias Föll*

Konferenzen und Summer Schools

Konferenzvorträge

2020 Lunch Seminar (Universität zu Köln); IAAEU Workshop on Job Security & Employment Protection (online); Spring Meeting of Young Economists (geplant); EEA VIRTUAL 2020 (online); Verein für Socialpolitik 2020 (online); Theories and Methods in Macroeconomics (Aix-en-Provence, vom Veranstalter abgesagt); 10th Search and Matching Annual Conference (Kopenhagen,vom Veranstalter abgesagt)

2019 Lunch Seminar (Universität zu Köln); International Conference on Technology, Demographics, and the Labor Market (Köln); Spring Meeting of Young Economists (Brüssel); 9th Search and Matching Annual Conference (Oslo); Midwest Macroeconomics Meeting (Athens, GA); 22nd IZA Summer School in Labor Economics (Ammersee); EEA-ESEM 2019 (Manchester); 31st EALE Conference (Uppsala, Co-Autor); Verein für Socialpolitik 2019 (Leipzig, Co-Autor); Frontiers (University of Edinburgh); IWH/IAB-Workshop (Halle, Co-Autor); AASLE 2019 (Singapur)

2018	Lunch Seminar (University of Cologne); Working Lunch (Barcelona GSE)
2014	2. Würzburger Ordnungstag: Distribution and Current Economic Policy (Frankfurt)

Summer Schools

06/2019	22nd IZA Summer School in Labor Economics , Prof. Dan A. Black, PhD; Prof. Judith K. Hellerstein, PhD
06/2018	Barcelona GSE Summer School of Economics, *Kurs: Labor Market Outcomes*, Prof. Robert Shimer, PhD
08/2017	LSE Methods Summer Programme, *Kurse: Tools for Macroeconomists: Essentails; Tools for Macroeconomists: Advanced Tools*, Prof. Wouter den Haan, PhD
05/2014	Kiel Institute PhD Supplementary Courses, *Kurs: Institutions and Development*, Kursleiter: Prof. James Robinson, PhD

Lehrerfahrung

Seit 04/2020	Übung zu *Wirtschaftspolitik II: Arbeitsmarkt- und Konjunkturpolitik*, Bachelorkurs, für Prof. Michael Krause, PhD
Seit 04/2017	Übung zu *Basismodul Makroökonomik für Betriebswirte*, Bachelorkurs, für Prof. Johannes Pfeifer, PhD
Seit 04/2017	Betreuung von Bachelorarbeiten
Seit 10/2016	Fieldseminar in *Growth, Education and Inequality in the Global Economy*, Masterseminar, für Prof. Michael Krause, PhD

Weitere Kenntnisse

IT-Kenntnisse

Microsoft Office	Regelmäßige Anwendung seit 12 Jahren (sehr gute Kenntnisse)
LaTeX	Tägliche Anwendung seit 5 Jahren (sehr gute Kenntnisse)
MATLAB	Regelmäßige Anwendung seit 5 Jahren (gute Kenntnisse)
Dynare	Anwendung während mehrerer Forschungsprojekte (gute Kenntnisse)
Stata	Anwendung während mehrerer Forschungsprojekte (gute Kenntnisse)
SAP	Regelmäßige Anwendung während der Ausbildung (gute Kenntnisse)
R	Anwendung während mehrerer Forschungsprojekte (Grundkenntnisse)

Sprachen

Deutsch	Muttersprache
Englisch	Verhandlungssicher in Wort und Schrift
Französisch	Grundkenntnisse
Spanisch	Grundkenntnisse

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nach § 8 Abs. 3 der Promotionsordnung vom 17.02.2015

"Hiermit versichere ich an Eides Statt, dass ich die vorgelegte Arbeit selbstständig und ohne die Benutzung anderer als der angegebenen Hilfsmittel angefertigt habe. Die aus anderen Quellen direkt oder indirekt übernommenen Aussagen, Daten und Konzepte sind unter Angabe der Quelle gekennzeichnet. Bei der Auswahl und Auswertung folgenden Materials haben mir dienac hstehend aufgeführten Personen in der jeweils beschriebenen Weise entgeltlich/unentgeltlich (zutreffendes unterstreichen) geholfen:

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Pulheim, 28.02.2021

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