Does Labor Market Flow Help or Hurt Firm Innovation? Evidence from OECD Countries

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Abstract

This paper investigates the interplay between labor market flow and corporate innovation. Leveraging the comprehensive job-to-job transition metric developed by Donovan et al. (2023), we find a negative and significant relationship between labor market flow and innovation, which is robust across various model specifications and endogeneity tests. We also find evidence supporting the labor adjustment cost channel as the predominant mechanism over the knowledge spillover channel, affecting innovation through labor market flow. We further show that the effect of labor mobility varies depending on the type and direction of labor movement, as well as industry characteristics. Our paper contributes to the literature on labor market flow and corporate innovation and holds important implications for firms and policymakers.

Keywords: Labor Market Flows, Corporate Innovation, Labor Adjustment Cost, Knowledge Spillover

JEL codes: G15, G32, E24

1. Introduction

Firms continuously strive to gain a competitive edge in their respective markets, aiming to bolster profitability through enhanced production and distribution processes. Central to this endeavor is innovation, a pivotal driver enabling firms to develop superior products and enhance operational efficiency and effectiveness (Audretsch, 1995). Within this context, labor emerges as a fundamental catalyst in shaping firms' innovation and production process, thereby underscoring the importance of investing in human capital across all firms. However, unlike tangible assets such as land or technology, firms exert limited control over labor, with workers possessing the flexibility to transition between firms and industries under certain contractual stipulations. This labor market flow, or mobility, captures the fluid movement of workers across job roles and transitions from self-employment to wage employment and vice versa, and profoundly influences firms' capital investments (Bai et al., 2023). Recent years have witnessed an amplification of this effect, propelled by the rapid pace of technological advancement, global interconnectedness, and heightened labor market competition (Zingales, 2000).

At its core, the impact of labor mobility on firm innovation manifests through two contrasting channels: labor adjustment cost and knowledge spillover. The departure of a worker increases firm expenses associated with search, recruitment, and training, thus resulting in heightened labor adjustment costs for the firms (Merz and Yashiv, 2007; Belo et al., 2014). The disruptions not only elevate the risk of project failure but also undermine the productivity of capital investments (Campbell et al., 2012; Baghai et al., 2021), with the firing costs of skilled personnel further exacerbating firms' operational burdens (Ghaly et al., 2017; Autor, et al., 1998). In parallel, economists have long observed that the interfirm mobility of labors transmits technological know-how across firms (Arrow, 1962; Stephan, 1996). Kerstetter (2000) and Hibbard (1998) illustrate how firms strategically poach talent to gain access to competitors' technologies, reflecting Silicon Valley's philosophy that "*If you have trouble with the competition, simply raid its talent*." Consequently, employee misappropriation of technological know-how adds to firms' labor adjustment cost, serving as a deterrent to operational efficacy and human capital investment, potentially stifling overall innovation. Accordingly, we hypothesize a negative association between labor market flows and corporate innovation attributable to labor adjustment costs. We term this view the *"labor adjustment cost*" (LAC) hypothesis.

Conversely, labor market flows can exert positive influences on innovation dynamics through the facilitation of free exchange of labor that fosters knowledge transfers across firms (Boeker, 1997). This enables firms to assimilate new operational and production insights from incoming hires, thereby enhancing productivity (Balsvik, 2011; Gorg and Strobl, 2005). Additionally, labor mobility empowers firms to explore diverse technological realms (Palomeras and Melero, 2010; Rosenkopf and Almeida, 2003; Tzabbar, 2009), cultivate novel product lines (Boeker, 1997; Rao and Drazin, 2002), and bolster R&D output (Ejsing et al., 2013). Parrotta and Pozzoli (2012) contend that these knowledge spillovers can lead to increased investment by enabling firms to identify new revenue streams or cost-saving avenues. Moreover, heightened mobility enhances employee-employer alignment (Audretsch and Feldman, 1996; Fredriksson et al., 2018), curbing recruitment costs and facilitating the acquisition of skilled workers (Starr et al., 2021). Thus, we posit an alternative hypothesis suggesting a positive impact of labor market flow on firms' innovation and name this view the "*knowledge spillover*" hypothesis.

While extant literature has extensively examined the impact of labor mobility on various financial metrics such as firms' financial leverage and investment rates (Sanati, 2023), firms' debt (Klasa, et al., 2018; Bai et al., 2022), and firm value (Shen, 2021), the impact of labor mobility on firm innovation remains relatively underexplored. Aligned with the knowledge transfer occurring among patent-active firms through the mobility of R&D workers, Kaiser et al (2015) offer insights into a positive relationship between R&D labor mobility and firms' innovative activities within Danish firms. Within a cross-country framework, our study aims to deepen our comprehension of the impact of labor job-to-job transitions between firms on corporate innovation activities, through the lenses of both the labor adjustment cost channel and the knowledge spillover channel.

We examine the relationship between labor market flows and corporate innovation across 11 OECD countries during the period 1980–2017.[1] Using the job-to-job transition measure constructed by Donovan et al. (2023) as the primary measure of labor mobility, and using patent counts and citations from the United States Patent and Trademark Office (USPTO) assembled by Bena et al. (2017) as proxies for innovation, we find a negative and significant relationship between overall labor market flows and innovation, in both number of patents and patent citations. In terms of economic significance, a one-standard-deviation increase in the percentage of job-to-job transition rate leads to a 18.71% (10.91%) decrease in the number of patents granted (citations). We control firm and year fixed effects to account for time-invariant firm characteristics and possible macroeconomic factors (e.g., financial crises and recessions) that may affect firm innovation. We also cluster standard errors at the firm level to account for potential correlations of the errors within each firm. To address potential endogeneity concerns, we employ both a staggered difference-in-differences approach to stack event-by-event based on shocks to LAC due to labor market counter-reforms, an independent external event to firms' innovation policy, and an instrumental

[1] The countries listed in our sample include USA, Austria, Switzerland, Spain, France, UK, Ireland, Italy, Luxembourg, Mexico, and Netherlands.

variable approach using labor market institutions as instrumental variables following Donovan et al. (2023), and the results still hold.

We examine the underlying economic channel that mediates the negative impact of labor mobility on firm innovation. We utilize three measures—labor market intensity, financial constraints, and labor cost—as proxies for labor adjustment costs. Labor market intensity reflects a firm’s workforce size relative to its total sales, indicating the scale of labor-related expenses (Li et al., 2020). Financial constraints represent a firm’s challenges in accessing external funds and capture the economic limitations that impede firms from efficiently managing labor mobility and investing in innovation (Whited and Wu, 2006; Denis and Sibilkov, 2010). Labor costs reflect the direct financial burden associated with labor mobility, including high wages, severance payments, and potential litigation costs (Ghaly et al., 2017; Autor et al., 1998; Wezel et al., 2006; Campbell et al., 2011). We find that labor mobility negatively affects innovation, especially in firms with higher labor market intensity, financial constraints and labor costs. Using major labor market counter-reform laws passed in six out of the eleven OECD countries in our sample as an exogenous shock, we find that the negative effect of labor mobility on innovation is more pronounced after the passage of counter-market reform laws, aligning with our LAC hypothesis.

When we decompose the job-to-job transition rate variable into two components (i.e., transition from wage work to self-employment and transition from self-employment to wage work), we find that the former decreases firms’ innovation, whereas the latter increases it. When a worker moves from wage work to self-employment, the firm loses that worker’s knowledge and know-how, incurring additional costs for hiring and training, as well as possible costs due to project disruption and failure, thus dampening innovation. This finding aligns with existing literature (Ghaly et al., 2017; Wezel et al., 2006). In the latter case, when workers transition from self-employment to wage work, these entrepreneurs contribute fresh knowledge, skills, and experience to the firms, thereby fostering innovation and lending support to the knowledge-sharing theory.

We perform heterogeneity tests on labor adjustment costs and find that the adverse impact of labor mobility on corporate innovation is stronger for firms in industries with higher labor adjustment costs. This highlights the relevance of the labor adjustment cost channel through which labor mobility affects firms' innovation: heightened labor adjustment costs associated with labor movement discourage firms from investing in innovation activities.

Our results are robust to alternative regression specifications, including Poisson regressions, to address concerns regarding count-based dependent variables (Cohn et al., 2022), as well as leading by 2- and 3- years for innovation measures. We also explore alternative model specifications that include clustering at the firm and year levels as well as specifications that control for year, industry, and country fixed effects. [2] Our results remain significant. Furthermore, when we exclude the USA—the country with the highest number of patents granted—from the baseline sample, our findings continue to be consistent.

This study contributes to the literature on the financial effects of labor market flows on firm innovation. Previous research has explored the impact of mobility shocks from changes in immigration policies and U.S. state-level regulations (i.e., non-competes and inevitable disclosure doctrines) on various firm-level outcomes, such as investment, leverage, acquisitions, venture capital investment, and entrepreneurship (Sanati, 2018; Jeffers, 2024; Garmaise, 2011; Younge et al., 2015; Starr et al., 2018; Chen et al., 2021; Kang and Fleming, 2019; Gu et al., 2020; Gupta, 2023). We utilize the job-to-job transition rate developed by Donovan et al. (2023), as a measure of global labor market flows for several reasons. First, it offers a comprehensive view of labor mobility by encompassing movements between

[2] These results are unreported for brevity and can be available upon request.

different job positions, including shifts from self-employment to wage work, changes in employers, and alterations in employment status. This broad perspective ensures that all forms of labor mobility are accounted for, providing a holistic understanding of workforce dynamics. Second, by leveraging a harmonized dataset from 11 countries worldwide, the job-to-job transition rate offers a new global outlook on labor market flows. Unlike immigration policy changes and U.S. state-level regulations, which are confined to specific regions, this rate allows for cross-country comparisons and insights into international labor mobility patterns. Third, from a firm's standpoint, the job-to-job transition rate is highly relevant as it reflects both the acquisition of new talent and the potential loss of valuable employees. Thus, analyzing job-to-job transitions enables firms to assess their ability to attract and retain skilled workers, crucial for sustaining innovation capacity and competitiveness.

Our paper also contributes to the innovation literature by lending support to previous studies emphasizing the effect of human capital on corporate innovation (Ederer and Manso, 2013; Balsmeier et al., 2017; Custodio et al., 2019; Chemmanur et al., 2019). Moreover, our study adds to the growing literature concerning the impact of labor market factors, such as stringent labor laws (Acharya et al., 2013; Francis et al., 2018), satisfying workplaces (Bloom et al., 2011), unionization (Bradley et al., 2017), general employee treatment (Chen et al., 2016), a diverse labor force (Page, 2007), and efficient wages (Akerlof, 1982; Akerlof and Yellen, 1990; Yellen, 1984), on corporate innovation. In this paper, we show that labor mobility across firms plays a significant role in shaping corporate innovation. However, the impact varies depending on the direction of labor movement. Specifically, we observe that transitions from wage work to self-employment tend to dampen firms' innovation efforts, while transitions from self-employment to wage work are associated with heightened innovation. These nuanced findings underscore the complex relationship between labor mobility and corporate innovation, suggesting that efforts to foster innovation within firms must consider the specific dynamics of labor movement.

Our findings contradict those of Kaiser, et al. (2015), which focus on a specific sample of Danish firms from the period 1999–2004. Kaiser et al. (2015) examine the interfirm movement of highly skilled workers and identify a positive impact on innovation from the knowledge transfer channel. In contrast, we employ a new measure of labor market flows which encompasses a more general labor market movement, harmonized from microdata labor force surveys worldwide. The sample in Kaiser et al. (2015) may more characteristically exhibit a knowledge spillover channel, similar to our finding of the transition of workers from self-employed to wage work.

The findings of this paper have significant economic implications for policymakers, firm managers, and shareholders. For policymakers, understanding the impact of labor mobility on corporate innovation is crucial for designing effective labor market policies. The negative association between labor market flows and corporate innovation, as unveiled in this study, underscores the importance of policies that promote labor market mobility while concurrently mitigating firms' labor adjustment costs, which may arise from expenses related to the recruitment and training of new hires and the brain drain of key workers. Initiatives aimed at easing labor transitions and incentivizing firms to retain skilled workers (e.g., through the use of employee stock options) can be instrumental in nurturing corporate innovation, ultimately enhancing economic growth and bolstering national competitiveness. For firm managers, these insights underscore the importance of strategic human capital management, emphasizing the necessity of customizing recruitment and retention strategies to mitigate negative effects while leveraging positive knowledge spillovers. Shareholders can benefit by gaining insights into factors driving firm innovation, allowing them to make more informed investment decisions and incentivize firms to prioritize long-term value creation and sustainability.

The remainder of this paper proceeds as follows: Section 2 provides a literature review and hypotheses development; Section 3 focuses on data and variable descriptions; Section 4 discusses the main findings and empirical analyses; and Section 5 concludes the paper.

2. Hypothesis development

Innovation is crucial for firm competitiveness, productivity, and long-run growth (e.g., Solow, 1957; Romer, 1986, 1990; Porter, 1992; Pakes, 1985; Austin, 1993; Hall et al., 2005; Kogan et al., 2017). Human capital is widely regarded as the engine of the innovation process (Acemoglu, 1996; Acemoglu et al., 2006; Aghion and Howitt, 1992; Aghion et al., 1998; Romer, 1990). Many studies have shown that labor market factors such as stringent labor laws (Acharya et al., 2013; Francis et al., 2018), satisfying workplaces (Bloom et al., 2011), unionization (Bradley et al., 2017), general employee treatment (Chen et al., 2016), a diverse labor force (Page, 2007), and efficient wages (Akerlof, 1982; Akerlof and Yellen, 1990; Yellen, 1984) are important determinants of corporate innovation. Recent studies also investigate how labor mobility influences firm innovation. For example, Kim and Marschke (2005) find that the risk of a scientist's departure reduces the firm's R&D expenditures and raises its propensity to patent an innovation. Kaiser et al. (2015) report a positive effect of mobility of highly skilled workers in Denmark on the patenting activity of both the origin and destination firms. Knowledge sharing theory posits that labor mobility fosters corporate innovations through interfirm knowledge transfer (DiMaggio and Powell, 1983; Almeida and Kogut, 1999; Mansfield, 1985; Kaiser et al., 2015). However, the frequent departure of mobile workers incurs greater training, recruitment costs and an increased risk of project failure (Diamond, 1982; Manning, 2003; Campbell et al., 2012; Blatter et al., 2012, 2016; Belo et al.,

2017) which may deter firm innovation due to salient labor adjustment costs. The critical link between the labor market mobility and corporate innovations cross countries is unclear. Given the conflicting arguments in the literature, we examine this issue with two competing hypotheses.

2.1 The labor adjustment cost (LAC) theory

Labor mobility empowers workers and disadvantages firms by eroding their competitive edge and transferring knowledge assets to competitors (Coff, 1997; Campbell et al., 2012). Frequent employee turnover exposes firms to substantial labor adjustment costs, which are significant and economically meaningful as labor market frictions (Diamond, 1982; Pfann and Palm, 1993; Hamermesh, 1989, 1995; Hamermesh and Pfann, 1996; Manning 2006; Dube, et al., 2010; Blatter et al., 2016).

First, firms incur high recruitment costs associated with advertising, searching for, screening, hiring, and training new employees (Oi, 1962; Hamermesh, 1995; Hamermesh and Pfann, 1996; Pissarides, 2011; Yashiv, 2007). The adjustment costs are higher for firms with higher hiring rates (Belo et al., 2017). It takes more time to replace skilled workers who are scarce (Oi, 1962), thus these costs are more salient for jobs that require advanced technical skills (Manning 2003; Dolfin 2006; Blatter, et al., 2012). Previous studies show that labor adjustment costs rise with labor expertise, particularly for firms that heavily depend on knowledgeable workers (Hamermesh and Pfann, 1996; Pfann and Verspagen, 1989; Ochoa, 2013; Dube et al., 2010; Belo et al., 2017; Blatter et al., 2016; Ghaly et al., 2017; Klasa et al., 2018). Know-how workers have the highest bargaining power as they have the best outside job options compared to other types (Sanati, 2023). To save on external hiring costs, firms may provide more apprenticeship positions and incur the internal training and retention costs (Blatter, et al., 2016).

Furthermore, employee departures at critical development stages can reduce capital productivity (Donangelo, 2014), and disrupt projects that require long-term development (Ghaly et al., 2017). Frequent turnover results in operating disruption costs such as vacancy costs and lost profits (Autor, et al., 1998), raises the risk of project failure and the loss of valuable human and social knowledge (Campbell et al., 2012; Wezel et al., 2006), lowers investment productivity (Shen, 2021), and increases firing costs such as severance pay and litigation costs (Dertouzos, et al., 1988; Autor et al., 2006). Taken together, these costs prevent firms from costlessly adjusting their labor stock (Belo, et al., 2014). As a consequence, firms encountering elevated labor adjustment costs may be deterred from hiring or firing, thereby influencing their investment in worker training and other forms of human capital development, particularly if these key personnel depart to join rival firms (Bertola, 1992; Starr, 2019).

The lack of full control over employees' human capital represents a source of risk for firms. Donangelo (2014) attributes the differences in risk premiums to the flexibility of labor mobility across employers and argues that the induced operating leverage amplifies firms' exposure to systematic risk. Sanati (2023) shows that labor mobility results in declining use of firm debt and investment rates, particularly for firms relying on skill workers. To avoid financial distress and prevent the departure of key workers, firms adopt conservative financial policies by holding more cash and carrying less debt (Brown and Matsa, 2016; Ghaly, et al., 2017). The inalienability of human capital results in higher labor costs of financial distress for firms relying on skilled workers, and the risk of talent loss contributes to these firms' conservative choice in capital structure (Baghai et al., 2021).

Endowed with deeper and broader R&D knowledge, the departure of key employees may have a larger adverse impact on patent-active firm performance than firms that do not patent. Firms may invest less in innovation and human capital development for their employees if their skilled workers leave and share ideas with competitors (Singh and Agrawal, 2011). Patents, as markers for innovation output, require a number of years to develop (Griffin et al., 2021). Firms with more patents are expected to have greater proprietary information associated with innovations (King et al., 1990). Job-hopping between companies increases the likelihood of knowledge leakage between rival firms, which can hamper firms' innovation activities (Fallick et al. 2006). Innovation typically involves prolonged resource commitment and entails a high level of uncertainty (Griffin et al., 2021). Given the potential loss of mobile workers, along with the significant labor adjustment costs and associated operation disruption, firms may exhibit greater risk adversion and have a propensity to curtail investment in innovation. Therefore, we conjecture the following hypothesis:

Hypothesis 1: *Labor market mobility is negatively associated with corporate innovation, all else being equal.*

2.2 The knowledge spillover theory

Another strand of literature suggests that labor mobility stimulates corporate innovations through interfirm knowledge transfer (DiMaggio and Powell, 1983; Almeida and Kogut, 1999; Mansfield, 1985; Kaiser et al., 2015). The mobility of key employees triggers the transfer of routines across organizational boundaries (Wezel et al. 2006). "Learning-by-hiring" is a prevalent strategy employed by firms to gain access to external technology (Levin et al., 1987; Palomeras and Melero, 2010; Rosenkopf and Almeida, 2003). Firms benefit from the knowledge and skills brought by new hires to increase productivity (Balsvik, 2011; Görg and Strobl, 2005), enter new product markets (Boeker, 1997), and surmount resource constraints on product innovation (Rao and Drazin, 2002). The mobility of inventors mitigates the difficulties of learning in firms across distinct technological areas (Parrotta and Pozzoli, 2012), contributes to knowledge diffusion by overcoming both geographic and technological constraints (Rosenkopf and Almeida, 2003; Tzabbar, 2009), and boosts hiring firms' subsequent innovation productivity (Hoisl, 2007; Ejsing et al., 2013; Hoisl, 2007; Jain, 2016; Kaiser et al., 2015; Kaiser et al., 2018).

Furthermore, mobile workers may continue to contribute to the previous employer's innovation output. As evidenced by the hiring firms' citations to the recruits' pre-move patents, Singh and Agrawal (2011) find that hiring firms exploit the prior inventions of new hires. The departure of key employees may increase the former employer's awareness to the hiring firm, particularly regarding the new firm's R&D activities (Corredoira and Rosenkopf, 2010). The social tie between mobile workers and their former co-workers facilitates knowledge exchange among firms. The reverse knowledge transfer alleviates the knowledge loss experienced by the former employer when skilled workers depart (Kaiser et al., 2015), and translates into positive effects on the previous employer's patent productivity (Agrawal et al., 2006; Corredoira and Rosenkopf, 2010; Godart et al., 2014).

Kambourov and Manovskii (2009) find that labor mobility is driven by the level of occupation-specific human capital. Topel and Ward (1992) observe that labor mobility increases the match quality between employer and employee by repositioning skills and abilities. The better employee-employer matches boost the productivity of invested capital and increase a project's value (Anand et al., 2018; Fredriksson et al., 2018) and increase searching efficiency by hiring employees with relevant skills and experience (Starr et al., 2021). As a result, labor mobility may lead to more investments by increasing the expected value of new projects or by reducing operation and labor costs (Parrotta and Pozzoli, 2012; Bai et al., 2023). The above discussion leads to our second baseline hypothesis:

Hypothesis 2: *Labor market mobility is positively associated with corporate innovation, all else being equal.*

3. Data and variable descriptions

3.1 Data sources and sample selection

We obtain firm patent information from the United States Patent and Trademark Office (USPTO), assembled by Bena et al. (2017), in a project named the Global Corporate Patent Dataset (GCPD). Global job-to-job transition rate data are collected from Donovan et al. (2023). Firm-level accounting data are extracted from Compustat North America and Global Annual, and macroeconomic data from the World Bank's World Economic Indicators. Our sample comprises 11 OECD countries including Austria, France, Ireland, Italy, Luxembourg, Mexico, Netherlands, Spain, Switzerland, the United Kingdom, and the United States.[3] The sample spans from 1980 to 2017 due to the availability of innovation data.

Following prior studies on firm innovation (Bena et al., 2017), we exclude financial firms (SIC codes: 6000–6999) and utility companies (SIC codes: 4900–4999) because their operations are subject to industry-specific regulations. Firms that have negative assets or negative sales are also excluded. We further require that publicly listed firms have at least ten patents (in total) over the sample period. The final sample consists of 21,694 unique firms for a total of 197,574 firm-year observations.

3.2 Global labor mobility: job-to-job transition rate

To measure labor mobility, we utilize the job-to-job transition rate, compiled by Donovan et al. (2023). To construct this measure, Donovan et al. (2023) employ a harmonized dataset that combines microdata from rotating panel labor force surveys conducted in 42 countries around the world. Donovan et al. (2023) first construct labor force status by creating a standardized definition applied consistently to the original microdata for all countries and years. This is essential because the provided labor force status variable is subject to variations

[3] Several innovative OECD countries, including Australia, Canada, Germany, Switzerland, and Singapore, are not included in our sample due to the absence of global labor mobility data.

across countries and over time. To achieve this standardization, they categorize individuals into three primary groups:

- Employed: People who are engaged in the production of goods and services within the production boundary, as defined by the System of National Accounts. This group includes wage and salary workers, as well as the self-employed individuals, which encompasses employers, own-account workers, and unpaid family workers.
- Unemployed: People who are not employed but meet the standard three-part test, which includes wanting a job, actively searching for a job in the last four weeks, and being available to start a job.
- Inactive (Out of the Labor Force): Individuals who do not meet any of the two criteria mentioned above.

Donovan et al. (2023) then use reported changes in labor force status to measure labor market flows and transitions. They construct three key rates: the job-finding rate, the employment-exit rate, and the job-to-job transition rate. The job-to-job transition rate captures the share of initially employed individuals who change jobs in the subsequent quarter. This rate encompasses various scenarios, including workers transitioning from self-employment to wage work, those shifting from wage work to self-employment, and wage workers changing employers.

We employ job-to-job transition as the primary measure of labor mobility in our analysis, as it offers several compelling advantages. First, unlike other measures of labor market flows, job-to-job transition is particularly pertinent from a firm's point of view because it represents not only the acquisition of new talent but also the potential loss of valuable employees. Hence, analyzing job-to-job transitions provides insights into how firms gain and lose employees, especially those with specific skill sets, knowledge, and experience, which are often critical for the innovation capacity of firms. Second, understanding job-to-job transitions can inform labor market policies and strategies to promote labor mobility and innovation. Policies that support smooth labor transitions and encourage firms to attract and retain top talent can be vital for fostering innovation.

3.3 Corporate innovation data

Existing literature has developed two proxies to capture firm innovation: R&D expenditures (i.e., innovation input) and patenting activity (i.e., innovation output). However, the former measure has several shortcomings when used in a global context. First, not all investments in R&D result in successful patents. Second, varying accounting standards implemented across countries result in not all firms being obligated to disclose R&D expenditures in their financial statements. Missing R&D expenditure does not necessarily imply that firms are not engaging in innovative activities (Koh and Reeb, 2015). We thus rely on patent information (patent count and patent citations) to capture firms' innovation output. Prior research has argued that patent information is the most significant measure of a firm's innovation output (Griliches, 1979; 1991).

The patent information obtained from Bena et al. (2017) comes from a project named the Global Corporate Patent Dataset (GCPD). The GCPD employs internet searching engines to complement Bena et al.'s (2017) fuzzy-matching methodology, matching patent assignee strings with the domain names associated with each string. The final sample matches information of 3.2 million patents granted by the USPTO to the names of 9,200 publicly listed firms from 50 countries around the world from 1980 to 2017.

We obtain annual information on patent assignee names, the number of patents, the number of citations received by each patent, a patent's application year, and a patent's grant year, among others. Using this information, we construct two measures of a firm's innovation productivity. The first is the number of patent applications a firm files in a year that are eventually granted. Instead of its grant year, we measure a patent by its application year, as the application year is argued to more accurately reflect the actual time of innovation (Griliches et al., 1988). To further assess a patent's influence, we construct a second measure of corporate innovation productivity by counting the number of non-self-citations each patent receives in subsequent years. This measure is preferred for assessing the quality of a patent because it captures the economic value of innovation, distinguishing between breakthrough innovation and incremental discoveries. Following existing innovation literature (Hall et al., 2001; 2005), we adjust the two measures of innovation to address the truncation problems associated with the patent database. Specifically, we use the "fixed effects" method, which scales patents and patent citations by the average number of patent citations in the same group (year, technology class, or year-and-technology class) to which a patent belongs. To reflect the long-term nature of investment in innovation, both measures of innovation productivity are assessed one year ahead in the future.

3.4 Measuring control variables

In line with the existing literature on corporate innovation, we control for a comprehensive set of firm- and country-level factors that could impact a firm innovation output. At the firm level, we control for firm size (*SIZE*), measured by the natural logarithm of the firm's total assets; firm age (*AGE*), measured by the natural logarithm of the number of years since the year the firm first appeared in Compustat; investment in fixed assets (*CAPEX*), measured by total expenditures scaled by total assets; asset tangibility (*PPE*), measured by net property, plan, and equipment scaled by total assets; leverage (*LEV*), measured by total debt to total assets; profitability (*ROA*), return on total assets; sale growth (*SALE_GROWTH*), measured by the difference between the natural logarithm of total sales and the natural logarithm of the previous year's total sales; product market competition (*HHI*), measured by the sales-based Herfindahl–Hirschman Index; and investment in innovation (*R&D*), measured by R&D expenditure scaled by total assets.

At the country level, we consider several factors that may influence firm innovation. Specifically, we include the natural logarithm of gross domestic product per capita (*GDP*); economic growth (*GDPGROWTH*), measured by yearly growth rate of GDP; and foreign direct investment (*FDI*), measured as the absolute values of net inflows and outflows of foreign direct investments as a percentage of GDP. Because Hsu et al. (2014) find that financial development is related to innovation, we control for credit market development, which is the ratio of a country's domestic credit to its GDP (*FD*). We also control for equity market development using the ratio of a country's stock market capitalization to GDP (*STOCK*). Appendix Table A1 provides detailed variable definitions of the variables.

3.5 Summary statistics

Table 1 Panel A reports the mean values of both the country- and firm-level variables employed in this study for each country. The results highlight variations in job-to-job transition rates across countries, with Luxembourg exhibiting the highest rate at 0.031, while Mexico records the lowest rate at 0.003, indicating different frequencies of job transitions. In terms of innovative productivity, Ireland emerges as the most innovative country, with each firm filing an average of 88.521 patents annually, and their patents receiving an average of 125.189 citations. Conversely, Mexico is the least innovative, with firms filling only an average of 1.307 patents during the sample period. Consistent with prior research, the U.S. has the highest representation in our sample, comprising 162,087 firm-year observations, while Luxembourg has the smallest number of firms, with a mere count of 74 firm-year observations.

[Insert Table 1 here]

Table 1, Panel B, presents firm-level summary statistics, revealing an average of 34.435 patents (36.026 citations) per firm, with a notable standard deviation of 162.719 (166.561). This variation aligns with the heterogeneous nature of firm innovation in the global market, as observed in existing literature (Griffin et al., 2021; Luong et al., 2017). The mean job-to-job transition rate is 0.024 with a standard deviation of 0.019.

4. Empirical results

4.1 Baseline results

As a starting point, we employ a regression model to estimate the impact of labor market mobility on firm innovation. The model is presented as follows:

$$INNOVATION_{i,c,t+1} = \alpha + \beta_1 LABOR\ MOBILITY_{c,t} + \beta_2 Firm\ Controls_{i,c,t} + \beta_3 Macro\ Controls_{c,t} + \nu_i + \mu_t + \varepsilon_{i,c,t+1}, \quad (1)$$

where the indices *i*, *c*, and *t* represent firm, country, and year, respectively. The dependent variable, *INNOVATION*, comprises two key metrics: *LNPATS*, the natural logarithm of one plus the number of patents filed and eventually granted; and *LNCITE*, the natural logarithm of one plus the number of non-self-citations. *LABOR MOBILITY* is measured by the job-to-job transition rate, which captures the proportion of employed individuals who change their jobs in the subsequent quarter. We also incorporate *Firm Controls* and *Macro Controls*, which encompass vectors of firm- and country-level characteristics discussed earlier in Section 3.4. To account for time variations in innovation and the effect of omitted time-invariant firm-specific factors on innovation, we include year and firm fixed effects. As *INNOVATION* is likely to be autocorrelated over time, we mitigate this by clustering standard errors by firm to prevent inflated *t*-statistics, following Peterson (2009). Detailed variable definitions are available in Appendix A1.

In Table 2, we report the effect of labor mobility on the number of patents a firm file (and eventually grants) (*LNPATS*) and the number of non-self-citations (*LCITE*). Columns (1) to (6) present the regressions associated with Equation (1). Specifically, Columns (1) and (2) include only *LABOR MOBILITY*, firm fixed effects, and year fixed effects. Macroeconomic-level control variables are further introduced in Columns (3) and (4). Finally, firm-level control variables are also incorporated in Columns (5) and (6). Across all models, the coefficient estimates of *LABOR MOBILITY* are negative and statistically significant, and the result is also economically significant. The results in columns (5) and (6) show a one standard deviation increase in labor mobility (0.019) will lead to a decrease of 0.07 (= 3.705*0.019) in *LNPATS* and 0.037 (=1.964*0.019) in *LNCITES.* With a sample mean of *LNPATS (LNCITES)* equal to 0.374 (0.339), the effect is clearly significant, corresponding to 18.71% (10.91%) of its mean value. In other words, one standard deviation increase in labor mobility leads to 18.71% decrease in numbers of patents and 10.91% decrease in numbers of patent citations in one year.

[Insert Table 2 here]

The coefficients of control variables are mostly consistent with the previous literature (e.g., see Hall and Lerner (2010) for a survey). Capital expenditures are positively associated with innovation output, while firms with higher leverage tend to have lower levels of innovation. Surprisingly, the coefficient for return on assets (*ROA*) is negative and statistically significant, in contrast to the common belief that profitable firms are relatively more innovative. This finding contradicts Fang et al. (2014) but aligns with Luong et al. (2017). Country-level control variables indicate that firms in countries with higher GDP growth spurs innovation. Conversely, firms located in countries with more developed equity markets and financial systems exhibit lower innovation output. Additionally, there is evidence of a negative effect of foreign direct investment and GDP per capita on firm innovation, which is consistent with the findings of Luong et al. (2017).

4.2 Endogeneity tests

4.2.1 Difference-in-differences approach

We identify the effect of labor mobility on innovation through plausible exogenous variations in labor mobility. Specifically, we examine whether labor market counter-reforms that lead to an increase or tightening of employment protection intensify labor adjustment costs and, hence, influence the negative association between labor mobility and firm innovation. Table Appendix B provides a list of 6 out of 11 OECD countries that passed major labor market counter-reforms during 1980–2017 period. Intuitively, these counter-reforms introduce legal complexities, including specific procedures for hiring and firing, leading to increased administrative and legal expenses for firms.[4] Moreover, stricter regulations often require higher severance payments, adding a substantial financial burden and litigation costs. Firms may also become more cautious in investing in employee training and development, anticipating greater costs associated with employee turnover. Consequently, we anticipate that labor market counter-reforms may increase labor adjustment costs, thereby reinforcing the negative impact of labor market mobility on firm innovation.

Specifically, we employ a staggered difference-in-differences methodology that exploits the staggered adoption of labor market counter-reforms across 11 OECD countries to mitigate the possible confounding effects of omitted variables or unobserved differences between countries driving the estimate. Given that country-level labor market counter-reforms are largely independent of individual firms' innovation policy, exploiting such decisions comes close to a natural experiment. The first difference calculates the change in labor market conditions before and after the adoption of counter-reforms and their impact on firm innovation. The second difference assesses how a country's labor market counter-

[4] For example, the French government introduced the Social Modernisation Law in 2002, which significantly tightened the constraints on the dismissal of more than 10 employees and increased the obligations on employers to attempt to find alternative jobs for employees under threat of collective dismissal (Simintzi et al., 2015).

reforms influence firm innovation compared to those in countries that have not adopted the reform during a given period. We estimate the effect of labor market counter-reforms on firm innovation activities as the difference in these two differences.

To ensure the robustness of our results, we further employ a stacked event-by-event regression as an alternative research design. Recent studies raise concerns that standard staggered difference-in-differences regression treatment effects might be biased if already treated units are used as comparison units for later-treated units (e.g., Baker et al., 2022; Cengiz et al., 2019). Following the approach of Cengiz et al. (2019), we create a separate dataset for each labor market counter-reform, each excluding countries that have already adopted a reform from the remaining labor market reform years. In these datasets, we use an 11-year estimation window (from $t-5$ to $t+5$) around the respective adoption year and then stack these event-specific datasets in relative time to calculate an average treatment effect across these events.

[Insert Table 3 here]

The results of both the standard staggered difference-in-differences and the stacked event-by-event regressions are presented in Panel A of Table 3. *TREATED* is an indicator variable that equals one for countries adopting a labor market counter-reform, and zero otherwise. *POST* is a dummy variable equal to one for one to five years following a labor market counter-reform, and zero otherwise. Consistent with our baseline results, the interaction term *POST*×*TREATED* is negative and statistically significant across all models, implying that labor mobility reduces firm innovation output more after the passage of counter-market reforms. These results further strengthen our proposition that labor market mobility reduces firm innovation as they impose greater labor adjustment costs for firms, thereby disincentivizing those firms from engaging in innovation activities.

4.2.2 Instrumental variable approach

One may have concerns that our baseline regression results are driven by time-varying omitted variables that correlate with labor market mobility and corporate innovation. For example, country-level economic stability and government policies can collectively influence both labor mobility and innovation activities. Economically stable and thriving environments could induce greater labor mobility, as there are more opportunities to switch jobs, and workers have confidence in improving their job match. Moreover, stable economies provide a conducive setting for innovation, with firms having the financial security to invest in research and development. Government policies, such as labor laws and incentives for research and development, can also impact both labor mobility and innovation.

To mitigate this identification concern, we estimate our baseline regression model using an instrumental variable approach. We follow Donovan et. al. (2023) and employ labor market institutions as an instrumental variable for labor mobility. Donovan et. al. (2023) document that required severance payments reflect institutional arrangements for separations, lower the job-job transition rate. Existing literature also cites the importance of labor market institutions–the set of regulations, rules, and norms that affect employment relations in a country–for explaining cross-country differences in labor market mobility among wealthy countries (Ljungqvist and Sargent, 1998; Krause and Uhlig, 2012; Jung and Kuhn, 2014; Engbom and Moser, 2022). Therefore, we focus on several broad aspects of labor market institutions. Specifically, we obtain six sub-indices of labor market regulations from the 2022 annual report of the Economic Freedom of the World (EFW) introduced by the Fraser Institute (Gwartney et al., 2022): 1) hiring regulations and minimum wage, 2) hiring and firing regulations, 3) centralized collective bargaining, 4) hours regulations, 5) mandated cost of worker dismissal, and 6) conscription.[5] The sub-indices range from 0 to 10, with higher values indicating less government restriction on labor markets. For ease of interpretation, we multiple each sub-index by negative one to reflect greater labor market regulations. We then construct the first principal component of the six labor market regulation measures to avoid measurement errors associated with various labor market institutions. The degree of a country's labor market regulation is an appropriate instrumental variable because it is likely to be correlated with country-level labor market mobility and unlikely to be related to firm-level innovation, other than through its negative relation with labor market mobility.

Panel B of Table 3 presents the results of the IV estimation. Note that the sample size drops due to missing data on country-level labor market institution measures. In Column (1), the first-stage estimation results indicate that labor market regulation has a strong negative and significant relationship with labor market mobility. Also, the Kleibergen–Paap Wald *F*-statistic of 492.29 exceeds the Stock-Yogo critical value of 16.38 for weak instruments, rejecting the null hypothesis that the IV is weakly related to labor market mobility. In Columns (2) and (3), we report the second-stage results for *LNPATS* and *LCITE*, respectively. The coefficient on instrumented labor market mobility is negative and statistically significant at the 1% level for both innovation output measures, providing further support that our baseline findings are not driven by endogenous effects.

4.3 Economic channel: Labor adjustment cost (LAC)

In our next investigation, we delve into the role of labor adjustment costs as the underlying economic channel that mediates the negative impact of labor mobility on firm innovation. Labor adjustment costs encompass various expenses and potential risks incurred by firms

[5] The sub-indices are available for 165 jurisdictions from 1970 to 2021. These sub-components of labor market regulations are constructed based on data from the World Bank's Doing Business, the World Economic Forum's Global Competitiveness Report, the International Institute for Strategic Studies' Military Balance, the World Survey of Conscription and Conscientious Objection to Military Service produced by War Resisters' International, and various online sources. We thank the Fraser Institute for making these data available on the economic freedom website: www.fraserinstitute.org/economic-freedom/dataset.

when employees frequently switch jobs or leave the company. These costs include training and recruitment expenses, firing costs, operating disruption costs, and the costs associated with precautionary motives. Frequent employee departures lead to increased recruitment and training expenses, with the departure of skilled workers posing a risk of project delays (or failure) and knowledge loss, particularly if they join rival firms (Campbell et al., 2012). Firing costs, especially for skilled employees, discourage firms from making labor adjustments, while operating costs can significantly disrupt critical projects (Ghaly et al., 2017; Wezel et al., 2006). Furthermore, the influence of labor adjustment costs on risk aversion is evident, as firms that hold more cash to mitigate higher labor adjustment expenses tend to invest less in innovation (Ghaly et al., 2017). Consequently, these labor adjustment costs act as a deterrent, dissuading firms from allocating resources toward innovation, ultimately eroding their innovative capacity.

To investigate this conjecture, we employ the following regression model:

$$\begin{aligned} INNOVATION_{i,c,t+1} &= \alpha + \beta_1 LABOR\ MOBILITY_{c,t} + \beta_2 LABOR\ MOBILITY_{c,t} \times LAC_{i,c,t} \\ &+ \beta_3 LAC_{i,c,t} + \beta_4 Firm\ Controls_{i,c,t} + \beta_5 Macro\ Controls_{c,t} + \nu_i \\ &+ \mu_t + \varepsilon_{i,c,t+1.} \end{aligned} \quad (2)$$

The variables remain consistent with those defined earlier in Equation (1), except for the introduction of *LAC*, which consists of three proxies for labor adjustment cost: labor market intensity (*LABOR_INTENSITY*), financial constraints (*FIN_CONSTRAINTS*), and labor costs (*LABOR_COST*). First, labor market intensity reflects a firm's workforce size, measured by the number of employees scaled by total sales (Li et al., 2020).[6] Firms with a

[6] In unreported results, we adopt two alternative measures of labor market intensity and find consistent results. The first measure is the labor-capital ratio, defined as the number of employees (EMP) to the gross value of property, plant and equipment (PPEGT). The second measure is a low-tech firm dummy, which is set to one for firms with SIC codes that do not fall into the following categories: computer hardware (SIC codes 3571, 3572, 3575, 3577, and 3578), communications equipment (3661, 3663, and 3669), electronics (3671, 3672, 3674, 3675, 3677, 3678, and 3679), navigation equipment (3812), measuring and controlling devices (3823, 3825,

higher labor market intensity are more likely to allocate significant resources to labor-related expenses, such as hiring, training, and firing. This proxy thus captures the financial implications of labor adjustments and offers insights into how workforce size relates to labor adjustment costs and their influence on innovation.

Second, financial constraints pertain to a firm's increased cost of external financing or difficulty in accessing external funds (Whited and Wu, 2006; Denis and Sibilkov, 2010). Financial constraints encompass the potential difficulties that firms may face in managing labor adjustments, including the expenses associated with hiring, training, firing, and potential legal liabilities. When firms face financial constraints, they struggle to allocate resources efficiently, prioritize immediate financial stability, and become more risk-averse. Empirical research consistently shows that financially constrained firms tend to invest less in innovation and hold larger cash reserves as a precaution against unexpected costs (Almeida and Campello, 2007). As such, financial constraints effectively capture the economic limitations that hinder firms from managing labor adjustments and investing in innovation (Gorodnichenko and Schnitzer, 2013). For the measurement of financial constraints, we adopt the Whited and Wu (2006) financial constraint index.

Lastly, the loss of skilled employees induces high severance payments and can lead to significant litigation costs (Ghaly et al., 2017), operating disruption, and productivity losses (Autor et al., 1998; Wezel et al., 2006; Campbell et al., 2011), heightening the *LAC* for firms. We define *LABOR_COST* as a dummy variable equal to one if a firm's labor cost is above the sample median, and zero otherwise. A firm's labor cost is calculated as the ratio of staff expenses (XLR) to total assets (AT).[7] Following Donangelo et al. (2019), we first estimate the average staff expenses per employee (XLR/EMP) within each two-digit SIC industry for

3826, 3827, and 3829), medical instruments (3841 and 3845), telephone and related equipment (4812 and 4813), communications services (4899), and software (7371, 7372, 7373, 7374, 7375, 7378, and 7379); and zero otherwise (Loughran and Ritter, 2002). Low-tech firms are considered to be labor intensive.

[7] We find similar results using the ratio of staff expenses (XLR) to sales (SALE) and the ratio of staff expenses (XLR) to employees (EMP) as alternative measures of labor costs.

each year, using the available XLR observations. We then impute a firm's staff expenses as the product of the number of employees (EMP) and the average staff expenses per employee of the same two-digit SIC industry and year if the XLR value is missing. The higher a firm's average labor cost, the greater the potential *LAC* associated with the departure of skilled employees. Table 4 shows the empirical results for Equation (2).

[Insert Table 4 here]

The negative interaction terms in Table 4 confirm that labor mobility negatively affects innovation, particularly in firms characterized by greater labor market intensity (*LABOR_INTENSITY*), financial constraints (*FIN_CONSTRAINTS*), and labor costs (*LABOR_COST*). Thus, these findings provide empirical evidence supporting our labor adjustment cost channel, emphasizing that an increase in labor adjustment costs due to heightened labor market mobility leads to diminished firm innovation.

4.4 The labor adjustment cost channel: Exogenous shocks

To identify the *LAC* channel, we further exploit variations in labor adjustment costs through labor counter-reforms. We regress firm innovation on job transition, a labor counter-reform dummy, and their interaction. The negative and significant interaction term in Table 5 indicates that the labor market mobility's negative effect on innovation is stronger when firms experience labor counter-reforms, which intensify labor adjustment costs. This finding aligns with our *LAC* channel.

[Insert Table 5 here]

4.5 Effect of entrepreneurship on firm innovation

Expanding our analysis, we decompose the job-to-job transition rate into two components: transitions from wage work to self-employment (*WB_TRANSITION*) and transitions from self-employment to wage work (*BW_TRANSITION*). This approach allows us to disentangle the distinct impacts of these transitions on firm innovation dynamics. Specifically, the results in Columns (1) and (2) of Table 6 show that transitions from wage work to self-employment (*WB_TRANSITION*) are associated with a diminished number of patents. This might be attributed to the potential loss of skilled workers with valuable know-how when moving from established wage work positions to self-employment, disrupting ongoing projects and hindering knowledge continuity within firms. The negative association between transitions from wage work to self-employment and firm innovation aligns with the existing literature (Ghaly et al., 2017; Wezel et al., 2006), emphasizing the challenges and costs associated with such shifts, including training and recruitment expenses as well as the risk of project failure.

[Insert Table 6 here]

Conversely, transitions from self-employment to wage work (*BW_TRANSITION*) emerge as catalysts for heightened firm innovation, reflected in increased patent filings (*LNPATS*) and citations (*LCITE)*, as shown in Columns (3) and (4) of Table 6. This suggests that individuals transitioning from self-employment to wage work may bring diverse skills and experiences to their new roles within established firms, fostering an environment conducive to innovation. Overall, the analysis underscores the importance of distinguishing between these specific job transition types, shedding light on their differential effects on firm innovation. Such insights offer valuable guidance for policymakers and businesses in shaping effective labor market policies to promote innovation within firms.

4.6 Heterogeneity tests

4.6.1 Labor adjustment cost

To thoroughly explore the labor adjustment cost hypothesis, we utilize the labor skill index developed by Belo et al. (2017) (LAC index) as a metric for labor adjustment costs. Our investigation aims to determine whether the association between labor mobility and corporate innovation is more pronounced for firms operating in industries with higher labor adjustment costs. The LAC index is computed using the percentage of workers in occupations that require a high level of training and preparation using the Specific Vocational Preparation index from the Dictionary of Occupational Titles (DOT), provided by the Department of Labor. Employee data are obtained from the Bureau of Labor Statistics (BLS), Occupational Employment Statistics (OES) program. Although the index is based on U.S. firms' employee characteristics, we argue that, at the industry level, the labor skill dependency of U.S. firms should be similar to that of international firms in OECD countries.

Subsequently, we split our sample into two groups by ranking each firm according to their industry's LAC and assigning them to the high or low LAC sub-sample, depending on whether they fall within the top or bottom 50^{th} percentile of the annual LAC distribution, respectively. We then re-estimate Equation (1) separately for the two groups and present the regression results in Table 7. Notably, we observe negative coefficients of *LABOR_MOBILITY* for both high and low LAC sub-samples. The Chi-squared tests further indicate that the adverse impact of labor mobility on corporate innovation is more pronounced for firms in industries characterized by greater labor adjustment costs. These findings provide additional support for our hypothesis that labor adjustment costs serve as a disincentive, discouraging firms from dedicating resources to innovation and human capital development, ultimately diminishing their capacity for innovation.

[Insert Table 7 here]

4.7 Main results excluding the U.S.

To ensure that our findings are not dominated by the country with the largest representation in our sample, we exclude U.S. firms and rerun our main results presented in Tables 2 and 4. We find consistent results in Table 8.

[Insert Table 8 here]

4.8 Robustness tests

We supplement the baseline regression results in Table 2 with additional tests to ensure that our results are not sensitive to specific models or samples. Addressing concerns regarding count-based dependent variables (Cohn et al., 2022), we first employ a Poisson regression on the baseline model. These alternative approaches corroborate the main finding of a negative impact of labor mobility on firm innovation. Additionally, we explore alternative model specifications, including firm and year clustering as well as year, industry, and country fixed effects, to account for unobservable characteristics within industries and countries. These analyses produce consistent results and are reported in Table 9.

[Insert Table 9 here]

5. Conclusions

Our paper investigates the impact of labor market flow on corporate innovation using a sample of 11 OECD countries over the period from 1980 to 2017 and the labor market flow measure developed by Donovan et al. (2023). We find that labor market flow negatively affects corporate innovation. The underlying economic channel that mediates this negative effect of labor mobility on innovation is through labor adjustment costs, as firms must adjust when workers move in or out, incurring training and recruitment costs, firing costs, operation disruption costs, and costs arising from the firm's risk-averse behavior. Labor market flows hamper innovation, particularly in firms characterized by greater labor market intensity, financial constraints, and labor costs. Our baseline result suggests that the influence of this LAC channel dominates the effect of the knowledge spillover channel. However, when individuals transition from self-employment to wage work, it accentuates the impact of the knowledge spillover channel, consequently enhancing innovation. Our results stand up to various endogeneity tests, heterogeneity tests, and alternative model specifications.

Our paper extends the understanding of the relationship between labor market flow and corporate innovation. We document a pronounced negative relationship between labor market mobility and corporate innovation, particularly intensified by labor market counter-reforms. The utilization of the novel measure of labor market mobility proposed by Donovan et al. (2023) enables a more precise depiction of this association.

Our findings hold significance for both firms and government agencies. Firms can consider implementing strategies and policies aimed at retaining employees and minimizing labor adjustment costs. Such measures can enhance the productivity of their human capital investment and foster innovation. Meanwhile, government can implement appropriate regulations to mitigate the adverse impact of labor market flow on firms' investment in human capital and the innovation process.

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Table 1. Descriptive statistics

This table presents the descriptive statistics for all key variables used in the paper. Panel A reports the total number of observations, mean, standard deviation, minimum, 25th percentile, median, 75th percentile, and maximum values of all variables at the firm level. Panel B details the mean values of all country-level variables, broken down by country. Definitions of the variables are provided in Appendix A.

Panel A: Firm-level variables

Variables	**Obs.**	**Mean**	**Std. dev.**	**Min.**	**25th pct.**	**50th pct.**	**75th pct.**	**Max.**
LNPATS	197,574	0.374	0.954	0.000	0.000	0.000	0.000	4.796
LNCITES	197,574	0.339	0.947	0.000	0.000	0.000	0.000	4.840
LABOR_MOBILITY	197,574	0.024	0.019	0.000	0.000	0.030	0.041	0.059
SIZE	197,574	4.720	2.395	-0.761	3.028	4.655	6.375	10.423
AGE	197,574	2.384	0.819	0.693	1.792	2.398	2.996	4.025
CAPEX	197,574	0.062	0.071	0.000	0.018	0.039	0.078	0.400
PPE	197,574	0.281	0.237	0.002	0.088	0.214	0.412	0.911
LEV	197,574	0.270	0.306	0.000	0.045	0.206	0.379	1.933
ROA	197,574	-0.092	0.430	-2.932	-0.062	0.027	0.070	0.285
SALE_GROWTH	197,574	0.122	0.452	-1.481	-0.033	0.081	0.230	2.179
HHI	197,574	0.311	0.245	0.052	0.133	0.229	0.409	1.000
R&D	197,574	0.048	0.111	0.000	0.000	0.000	0.040	0.698
FC	197,574	-0.239	0.141	-0.581	-0.331	-0.243	-0.153	0.231
LABOR_INTENSITY	180,907	0.012	0.020	0.000	0.004	0.007	0.013	0.154
LABOR_COST	173,178	0.403	0.479	0.000	0.138	0.278	0.484	3.280
GDP	197,574	29.785	0.754	26.545	29.640	30.015	30.306	30.549
GDPGROWTH	197,574	0.026	0.019	-0.033	0.018	0.028	0.039	0.072
FD	197,574	1.415	0.369	0.260	1.137	1.377	1.754	2.064
STOCK	197,574	1.170	0.871	0.067	0.415	0.863	1.974	3.199
FDI	197,574	0.019	0.018	0.002	0.008	0.013	0.023	0.099

Panel B: Country-level variables

Countries	Obs.	NPATS	NCITES	LABOR_MOBILITY	GDP	GDPGROWTH	FD	STOCK	FDI
Austria	368	2.400	0.845	0.020	26.653	0.013	0.914	0.081	0.012

Czech Republic	1,216	44.052	22.366	0.020	27.230	0.020	1.627	1.154	0.050
France	6,781	50.277	20.165	0.010	28.468	0.011	0.896	0.603	0.019
Ireland	671	88.521	125.189	0.012	26.545	0.019	1.151	0.071	0.098
Italy	1,984	12.267	3.207	0.015	28.274	-0.003	0.861	0.558	0.013
Luxembourg	74	2.000	1.000	0.031	26.545	0.036	0.940	0.067	0.099
Mexico	1,751	1.307	0.922	0.003	27.609	0.026	0.271	0.086	0.027
Netherlands	141	137.588	98.560	0.007	27.258	0.021	1.164	0.868	0.099
Spain	1,527	5.172	2.041	0.021	27.786	0.013	1.431	0.898	0.028
United Kingdom	20,974	37.881	27.427	0.026	28.556	0.021	1.439	0.885	0.048
United States	162,087	33.967	36.078	0.025	30.103	0.028	1.454	1.260	0.014

Table 2. Baseline results

This table presents the results from regressions of firm innovation on labor mobility. Firm innovation is measured by LNPATS, which is the natural logarithm of one plus the number of patents filed and eventually granted, and LNCITE, which is the natural logarithm of one plus the number of non-self-citations. LABOR_MOBILITY is measured by the job-to-job transition rate, capturing the proportion of employed individuals who change their jobs in the subsequent quarter. *t*-Statistics with standard errors clustered at the firm level are reported in square brackets. ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively. Continuous variables are winsorized at the 1st and 99th percentiles. Detailed information regarding the construction of all variables is provided in Appendix A.

Dependent variable	LNPATS (t+1)	LNCITES (t+1)	LNPATS (t+1)	LNCITES (t+1)	LNPATS (t+1)	LNCITES (t+1)
	(1)	(2)	(3)	(4)	(5)	(6)
LABOR_MOBILITY	-1.850***	2.142***	-3.211***	-1.281***	-3.705***	-1.964***
	[-3.94]	[3.99]	[-9.10]	[-3.82]	[-9.84]	[-5.56]
SIZE					0.091***	0.073***
					[18.34]	[15.16]
AGE					0.027**	0.058***
					[2.44]	[4.89]
CAPEX					0.041*	0.058**
					[1.82]	[2.45]
PPE					-0.003	0.013
					[-0.14]	[0.62]
LEV					-0.025***	-0.039***
					[-3.05]	[-4.41]
ROA					-0.020***	-0.020***
					[-4.25]	[-3.82]
SALE_GROWTH					-0.005*	0.004
					[-1.82]	[1.32]
HHI					0.066***	0.060***
					[3.47]	[3.13]
R&D					0.236***	0.227***
					[7.27]	[6.08]
GDP			-1.348***	-2.426***	-1.403***	-2.370***
			[-7.34]	[-11.63]	[-7.47]	[-11.27]
GDPGROWTH			1.593***	1.235***	1.490***	1.086***
			[5.77]	[4.39]	[5.30]	[3.81]
FIN_DEVELOP			-0.095***	-0.074***	-0.111***	-0.091***
			[-4.49]	[-3.21]	[-5.11]	[-3.94]
STOCK			-0.01	-0.029***	0.001	-0.017**
			[-1.52]	[-4.39]	[0.09]	[-2.52]
FDI			-0.182	-0.841***	-0.104	-0.740***
			[-1.40]	[-6.37]	[-0.79]	[-5.58]
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Observations	197,574	197,574	197,574	197,574	197,574	197,574
Adj. R-squared	0.80	0.75	0.80	0.75	0.81	0.75

Table 3. Tests for endogeneity

This table reports the results of endogeneity tests. Panel A displays findings from staggered difference-in-differences (DiD) designs (Columns 1 and 2) and stacked event-by-event frameworks (Columns 3 and 4), based on shocks to labor adjustment costs due to labor market counter-reforms. Panel B reports the results of the instrumental variable analysis. Firm innovation is measured by LNPATS, which is the natural logarithm of one plus the count of patents filed and successfully granted, and LNCITE, which is the natural logarithm of one plus the number of non-self-citations. LABOR_MOBILITY is measured by the job-to-job transition rate, capturing the proportion of employed individuals who change their jobs in the subsequent quarter. TREATED is an indicator variable set to one for countries enacting labor market counter-reforms between 1997–2018, and zero otherwise. POST is a dummy variable equal to one for the initial five years following a labor market counter-reform, and zero otherwise. PC1 is the first principal component derived from six labor market regulation indicators. The regressions include the same control variables as in Columns (5) and (6) of Table 2. *t*-Statistics with standard errors clustered at the firm level are reported in square brackets. ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively. Continuous variables are winsorized at the 1st and 99th percentiles. Detailed information regarding the construction of all variables is provided in Appendix A.

Panel A: Exogenous shocks from labor market counter-reforms

	Staggered DiD		Stacked regression	
Dependent variable	LNPATS (t+1)	LNCITES (t+1)	LNPATS (t+1)	LNCITES (t+1)
	(1)	(2)	(3)	(4)
POST	0.007	0.019***	0.003	-0.004
	[1.25]	[3.05]	[0.47]	[-0.69]
TREATED	0.262***	0.266***	0.144**	0.162***
	[3.09]	[2.88]	[2.36]	[2.59]
POST × TREATED	-0.301***	-0.337***	-0.220***	-0.258***
	[-3.55]	[-3.69]	[-2.68]	[-3.03]
Controls	Yes	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
Observations	185,268	185,268	83,202	83,202
Adj. *R*-squared	0.81	0.75	0.89	0.85

Panel B: Instrumental variable analysis

	First-stage	Second-stage	
Dependent variable	LABOR_MOBILITY	LNPATS (t+1)	LNCITES (t+1)
	(1)	(2)	(3)
PC1	-0.0015***		
	[-22.19]		
LABOR_MOBILITY		-25.571***	-25.386***
		[-6.02]	[-5.41]
Controls	Yes	Yes	Yes

Firm FE	Yes	Yes	Yes
Year FE	Yes	Yes	Yes
Observations	97,130	97,130	97,130
Adj. *R*-squared	0.91	0.83	0.82
F-statistics on instrument	492.29		

Table 4. Labor adjustment costs

This table reports the results of the labor adjustment cost channel. Firm labor adjustment cost is proxied by labor market intensity (LABOR_INTENSITY), financial constraints (FC), and labor costs (LABOR_COST). Firm innovation is measured by LNPATS, which is the natural logarithm of one plus the count of patents filed and successfully granted, and LNCITE, which is the natural logarithm of one plus the number of non-self-citations. LABOR_MOBILITY is measured by the job-to-job transition rate, capturing the proportion of employed individuals who change their jobs in the subsequent quarter. The regressions include the same control variables as in Columns (5) and (6) of Table 2. *t*-Statistics with standard errors clustered at the firm level are reported in square brackets. ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively. Continuous variables are winsorized at the 1st and 99th percentiles. Detailed information regarding the construction of all variables is provided in Appendix A.

Dependent variable	LNPATS (t+1)	LNCITES (t+1)	LNPATS (t+1)	LNCITES (t+1)	LNPATS (t+1)	LNCITES (t+1)
	(1)	(2)	(3)	(4)	(5)	(6)
LABOR_MOBILITY	-7.446***	-5.258***	-4.945***	-3.044***	-6.345***	-2.198***
	[-11.10]	[-7.94]	[-9.01]	[-5.85]	[-8.67]	[-2.89]
LABOR_MOBILITY × FC	-10.097***	-8.893***				
	[-6.92]	[-6.13]				
FC	0.124**	0.113*				
	[2.17]	[1.94]				
LABOR_MOBILITY × LABOR_INTENSITY			-23.291***	-27.202***		
			[-4.57]	[-4.90]		
LABOR_INTENSITY			0.859***	0.979***		
			[4.83]	[5.03]		
LABOR_MOBILITY × LABOR_COST					-1.529***	-1.147***
					[-6.19]	[-4.64]
LABOR_COST					0.079***	0.066***
					[7.97]	[6.42]
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes

Observations	197,574	197,574	180,907	180,907	170,730	170,730
Adj. *R*-squared	0.81	0.75	0.81	0.75	0.81	0.76

Table 5. Shocks to labor adjustment costs

This table reports the results of the effect of exogenous shocks to labor adjustment costs from labor market counter-reforms on the association between firm innovation and labor mobility. Firm innovation is measured by LNPATS, which is the natural logarithm of one plus the count of patents filed and successfully granted, and LNCITE, which is the natural logarithm of one plus the number of non-self-citations. LABOR_MOBILITY is measured by the job-to-job transition rate, capturing the proportion of employed individuals who change their jobs in the subsequent quarter. POST_CREFORM is an indicator variable set to one for countries enacting labor market counter-reforms between 1997–2018, and zero otherwise. The regressions include the same control variables as in Columns (5) and (6) of Table 2. *t*-Statistics with standard errors clustered at the firm level are reported in square brackets. ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively. Continuous variables are winsorized at the 1st and 99th percentiles. Detailed information regarding the construction of all variables is provided in Appendix A.

Dependent variable	LNPATS (t+1)	LNCITES (t+1)
	(1)	(2)
LABOR_MOBILITY	0.166	0.161
	[0.92]	[0.99]
POST_CREFORM	0.286**	0.242*
	[2.09]	[1.95]
LABOR_MOBILITY × POST_CREFORM	-43.314***	-43.034***
	[-3.25]	[-3.30]
Controls	Yes	Yes
Firm FE	Yes	Yes
Year FE	Yes	Yes
Observations	27,852	27,852
Adj. *R*-squared	0.90	0.83

Table 6. Effect of entrepreneurship

This table presents the effect of entrepreneurial mobility on innovation in Panel A, and the impact of entrepreneurial mobility by education levels on innovation in Panel B. Firm innovation is measured by LNPATS, which is the natural logarithm of one plus the count of patents filed and successfully granted, and LNCITE, which is the natural logarithm of one plus the number of non-self-citations. LABOR_MOBILITY is measured by the job-to-job transition rate, capturing the proportion of employed individuals who change their jobs in the subsequent quarter. The regressions include the same control variables as in Columns (5) and (6) of Table 2. *t*-Statistics with standard errors clustered at the firm level are reported in square brackets. ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively. Continuous variables are winsorized at the 1st and 99th percentiles. Detailed information regarding the construction of all variables is provided in Appendix A.

Panel A: Effect of entrepreneurial mobility

Dependent variable	LNPATS (t+1)	LNCITES (t+1)	LNPATS (t+1)	LNCITES (t+1)
	(1)	(2)	(3)	(4)
WB_LABOR_MOBILITY	-1.613**	0.787		
	[-2.04]	[0.87]		
BW_LABOR_MOBILITY			4.190*	19.917***
			[1.70]	[7.68]
Controls	Yes	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
Observations	195,334	195,334	195,334	195,334
Adj. *R*-squared	0.81	0.76	0.81	0.76

Panel B: Effect of entrepreneurial mobility by high and low entrepreneurial education

Dependent variable	LNPATS (t+1)	LNCITES (t+1)	LNPATS (t+1)	LNCITES (t+1)
	(1)	(2)	(3)	(4)
EDUH_WB_LABOR_MOBILITY	-27.595***	9.659*		
	[-5.50]	[1.84]		
EDUL_WB_LABOR_MOBILITY	-14.897***	-17.443***		
	[-7.22]	[-7.49]		
EDUH_BW_LABOR_MOBILITY			9.202***	25.932***
			[3.82]	[10.36]
EDUL_BW_LABOR_MOBILITY			-30.230***	-21.390***
			[-6.71]	[-4.26]
Controls	Yes	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
Observations	195,334	195,334	195,334	195,334
Adj. *R*-squared	0.81	0.76	0.81	0.76

Table 7. Heterogeneity tests

This table presents the differential effect of labor mobility on innovation, comparing firms with high labor adjustment costs (LAC) to those with low LAC. Firm innovation is measured by LNPATS, which is the natural logarithm of one plus the count of patents filed and successfully granted, and LNCITE, which is the natural logarithm of one plus the number of non-self-citations. LABOR_MOBILITY is measured by the job-to-job transition rate, capturing the proportion of employed individuals who change their jobs in the subsequent quarter. The regressions include the same control variables as in Columns (5) and (6) of Table 2. *t*-Statistics with standard errors clustered at the firm level are reported in square brackets. ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively. Continuous variables are winsorized at the 1st and 99th percentiles. Detailed information regarding the construction of all variables is provided in Appendix A.

Dependent variable	LNPATS (t+1)		LNCITES (t+1)	
	(1) High LAC	(2) Low LAC	(3) High LAC	(4) Low LAC
LABOR_MOBILITY	-4.497*** [-7.53]	-2.410*** [-5.67]	-2.081*** [-3.89]	-1.426*** [-3.26]
p-value for equality of coefficients	0.025		0.072	
Controls	Yes	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
Observations	121,101	72,342	121,101	72,342
Adj. *R*-squared	0.82	0.84	0.76	0.78

Table 8. Results excluding U.S. firms

This table reports the results of the baseline regression and the labor adjustment cost channel, excluding U.S. firms. Firm labor adjustment cost is proxied by labor market intensity (LABOR_INTENSITY), financial constraints (FC), and labor costs (LABOR_COST). Firm innovation is measured by LNPATS, which is the natural logarithm of one plus the count of patents filed and successfully granted, and LNCITE, which is the natural logarithm of one plus the number of non-self-citations. LABOR_MOBILITY is measured by the job-to-job transition rate, capturing the proportion of employed individuals who change their jobs in the subsequent quarter. The regressions in Panel B include the same control variables as in Columns (5) and (6) of Table 2. *t*-Statistics with standard errors clustered at the firm level are reported in square brackets. ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively. Continuous variables are winsorized at the 1st and 99th percentiles. Detailed information regarding the construction of all variables is provided in Appendix A.

Panel A: Baseline Regression (Table 2)

Dependent variable	LNPATS (t+1)	LNCITES (t+1)	LNPATS (t+1)	LNCITES (t+1)	LNPATS (t+1)	LNCITES (t+1)
	(1)	(2)	(3)	(4)	(5)	(6)
LABOR_MOBILITY	-0.815***	-0.816***	-1.109***	-0.916***	-1.173***	-1.035***
	[-3.21]	[-2.94]	[-3.97]	[-3.18]	[-4.23]	[-3.61]
Controls	No	No	Country level	Country level	Firm and country level	Firm and country level
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Observations	35,487	35,487	35,487	35,487	35,487	35,487
Adj. *R*-squared	0.87	0.77	0.87	0.78	0.87	0.78

Panel B: Channel tests

Dependent variable	LNPATS (t+1)	LNCITES (t+1)	LNPATS (t+1)	LNCITES (t+1)	LNPATS (t+1)	LNCITES (t+1)
	(1)	(2)	(3)	(4)	(5)	(6)
LABOR_MOBILITY	-2.847*	-5.724***	-2.049***	-1.873***	-2.963***	-2.349***
	[-1.72]	[-3.10]	[-3.92]	[-3.53]	[-4.35]	[-3.63]

LABOR_MOBILITY × FC	-4.03	-11.289**				
	[-1.01]	[-2.54]				
FC	0.088	0.267**				
	[0.80]	[2.18]				
LABOR_MOBILITY × LABOR_INTENSITY			-0.824	0.273		
			[-1.02]	[0.57]		
LABOR_INTENSITY			31.959	-9.848		
			[1.06]	[-0.48]		
LABOR_MOBILITY × LABOR_COST					-2.930***	-4.627***
					[-3.03]	[-3.64]
LABOR_COST					0.078***	0.113***
					[3.35]	[3.58]
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Observations	35,487	35,487	25,890	25,890	29,458	29,458
Adj. *R*-squared	0.87	0.78	0.87	0.77	0.87	0.78

Table 9. Robustness checks

This table provides robustness test results. In Panel A, we control for firm- and year-fixed effects with clustering at the firm and year levels. In Panel B, we employ a Poisson regression model to investigate the association between labor mobility and corporate innovation. Firm innovation is measured by LNPATS, which is the natural logarithm of one plus the count of patents filed and successfully granted, and LNCITE, which is the natural logarithm of one plus the number of non-self-citations. LABOR_MOBILITY is measured by the job-to-job transition rate, capturing the proportion of employed individuals who change their jobs in the subsequent quarter. POST_CREFORM is an indicator variable set to one for countries enacting labor market counter-reforms between 1997–2018, and zero otherwise. The regressions include the same control variables as in Columns (5) and (6) of Table 2. In Panel B, *t*-Statistics with standard errors clustered at the firm level are reported in square brackets. ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively. Continuous variables are winsorized at the 1st and 99th percentiles. Detailed information regarding the construction of all variables is provided in Appendix A.

Panel A: Clustering at the firm and year levels

Dependent variable	LNPATS (t+1)	LNCITES (t+1)
	(1)	(2)
LABOR_MOBILITY	-5.908***	-3.766***
	[-10.77]	[-7.75]
Controls	Yes	Yes
Firm FE	Yes	Yes
Year FE	Yes	Yes
Observations	197,369	197,369
Adj. *R*-squared	0.31	0.27

Panel B: Poisson regression

Dependent variable	LNPATS (t+1)	LNCITES (t+1)
	(1)	(2)
LABOR_MOBILITY	-12.140***	-18.930***
	[-2.81]	[-3.03]
Controls	Yes	Yes
Firm FE	Yes	Yes
Year FE	Yes	Yes
Observations	75,270	70,517
Pseudo *R*-squared	0.44	0.45

Table A.1 Variable definitions

Variable	Definitions	Data Sources
Panel A; Firm Innovation Outputs		
LNPATS	Natural logarithm of one plus the number of patents filed and eventually granted.	Bena et al. (2017) & Global Corporate Patent Dataset
LCITE	Natural logarithm of one plus the number of non-self-citations.	Bena et al. (2017) & Global Corporate Patent Dataset
Panel B: Labor Mobility		
LABOR MOBILITY	Job-to-job transition rate which captures the proportion of employed individuals who change their jobs in the subsequent quarter.	Donovan et al. (2023)
WB_TRANSITION	Job-to-job transition rate which captures the proportion of employed individuals who change from wage worker to self-employment in the subsequent quarter.	Donovan et al. (2023)
BW_TRANSITION	Job-to-job transition rate which captures the proportion of employed individuals who change from self-employment to wage worker in the subsequent quarter.	Donovan et al. (2023)
Panel C: Firm- and industry- control variables		
SIZE	Natural logarithm of firm's total assets.	Compustat global & North America
AGE	Natural logarithm of the number of years since the year the firm first appeared in Compustat.	Compustat global & North America
CAPEX	Capital expenditure (capx) scaled by total assets (at)	Compustat global & North America
PPE	Net property, plant, and equipment (ppent) scaled by total assets (at)	Compustat global & North America
LEV	Firm i's leverage ratio, defined as book value	Compustat global

	of debt (long term (dltt) + short term (dlc)) divided by book value of total assets (at)	& North America
ROA	Return on assets defined as operating income before extraordinary items (ib) divided by total assets (at).	Compustat global & North America
SALE_GROWTH	Difference between the natural logarithm of total sales and the natural logarithm of the previous year’s total sales.	
HHI	Herfindahl index of 4-digit Standard Industrial Classification (SIC) industry to which firm belongs to, measured at the end of fiscal year.	Compustat global & North America
R&D	Research and development expenditures (xrd) scaled by total asset (at)	Compustat global & North America
Panel D: Country-level variables		
GDP	Natural logarithm of gross domestic product per capita.	WDI database
GDPGROWTH	GDP growth rate in a given year	WDI database
FDI	Foreign Direct Investment calculated by sum of absolute values of net inflows and outflows of foreign direct investments as percentage of GDP.	WDI database
FD	Ratio of a country’s domestic credit to its GDP	WDI database
STOCK	Ratio of a country’s stock market capitalization to GDP	WDI database
Panel E: Other variables		
TREATED	Dummy variable that equals one for countries adopting a labor market counter-reform, and zero otherwise.	
POST	Dummy variable equal to one for one to five years following a labor market counter-reform, and zero otherwise.	
LABOR_INTENSITY	The number of employees scaled by total sales	Li et al. (2020)
FIN_CONSTRAINTS	−0.091*cfo − 0.062*(1 if dv>0, 0 otherwise) +	Whited and Wu

	0.021 *(dltt/at) − 0.044[ln(at)] − 0.035*[($sale_t$-$sale_{t-1}$)/$sale_{t-1}$)]	(2006)
LABOR_COST	*A* dummy variable equal to one if a firm's labor cost is above the sample median, and zero otherwise. A firm's labor cost is calculated as the ratio of staff expenses (xlr) to total assets (at).	Donangelo et al. (2019)
LAC	The percentage of workers in occupations that require a high level of training and preparation.	Belo et al. (2017)
Panel F: Labor market institution variables		
Hiring regulations and minimum wage		Economic Freedom of the World, Fraser Institute
Hiring and firing regulations		Economic Freedom of the World, Fraser Institute
Centralized collective bargaining		Economic Freedom of the World, Fraser Institute
Hours regulations		Economic Freedom of the World, Fraser Institute
Mandated cost of worker dismissal		Economic Freedom of the World, Fraser Institute
Conscription		Economic Freedom of the World, Fraser

Institute

Table A2: List of Major Labor Market Counter-Reforms			
Countries	**Year**	**Legislations**	**Descriptions**
Austria	1988	Federal Act amending the Labor Constitution Act	A 1988 law increased the protection of workers with temporary contracts. In particular, the law changed the conditions under which the employees are placed at the disposal of third parties. It also outlawed agreements that are at the disadvantage of the employee. Sources: LABREF, OECD (Simintzi et al., 2014)
France	2003	Social Modernisation Law	…government introduced the Social Modernisation Law in 2002, significantly tightening the constraints on dismissal of more than 10 employees...in 2003 the new government suspended some of these provisions before introducing another law in 2004 which, while moderating some aspects of EPL, increased the obligation on employers to try to find alternative jobs for employees under threat of collective dismissal… The law permits "economic" dismissal only if it is necessary to preserve the competitiveness of the firm. Financial rationalisation by the management is not sufficient justification…in 2002 the Social Modernisation Law added a provision requiring that the financial position of the group to which the firm belongs should be taken into account, which means that an economic dismissal is not legally justified if the group is healthy. (pg. 105, 2005)
Ireland	2012	The Protection of Employees Act	Before 2012, the Government paid a rebate to employers for redundancy payouts to employees. Up until 1 January 2012 this rebate amounted to 60%; between 1 January 2012 and 1 January 2013, the Government rebate was 15%; from 2013 onwards the Government rebate was abolished [see e.g. https://www.eurofound.europa.eu/observatories/emcc/erm/legislation/ireland-severance-payredundancy-compensation] (IMF)
Italy	1991	Law on collective redundancies	In 1991, a law on collective redundancies was passed. The employer has the duty to inform union representatives about the reasons for the proposed layoffs. In particular, the employer needs to show the unions that it is not possible to take alternative measures to the intended dismissals. The employer also needs to describe the measures that are planned to mitigate the social consequences of the collective dismissal. The unions may request an examination of the reasons for the layoffs and the possibilities of

			utilizing the workforce in different ways within the firm. If the parties fail to reach an agreement, the next step is a conciliation phase conducted by the Labor Office. Failure to follow the procedure properly is penalized by the obligation to reinstate the employees who have thus been dismissed unlawfully. Source: fRDB, EIRO (Simintzi et al., 2015)
Switzerland	1994	New provisions for collective redundancies	An increase in EPLhappened in 1994. New provisions on collective redundancies apply to an employer if at least 10% of the workforce are dismissed. The employer has an obligation to give advance notice to employees or their representatives of the collective redundancy and the reasons for it. The representatives may make proposals on how the dismissals could be avoided or reduced but cannot block the dismissals. After consultation with employees or their representatives, the employer has to notify the cantonal employment office of the intended redundancies and the results of the consultation process. The sanctions for failure to consult will be fixed by a judge and may not exceed an amount equal to twice the employee's monthly salary.
USA	1989	The WARN Act (Federal law)	There was an increase in EPL in 1989. The WARN Act was a federal law that required employers to give written notice of 60 days, before the date of a mass layoff or plant closing, to affected workers, the chief elected official of the local government where the employment site is located, and the State Rapid Response Dislocated Worker Unit. Subject to the law are private employers with 100 or more full-time employees. In the case of noncompliance, employees, their representatives, and units of local government can bring lawsuits against employers. Employers who violate theWARNAct are liable for damages in the form of back pay and benefits to affected employees. Source: Levine (2007), Simintzi et al. (2015)