Title: Labor Adjustment Costs and Competitive Advantage: The Role of Health Insurance Benefits

Ulya Tsolmon (Washington University in St. Louis and Dan Ariely (Duke)

Provision of health insurance benefits has been an important human capital management policy dilemma for firms and a hotly debated subject in the public policy arena. Growing research has focused on the role of workplace wellness practices in increasing worker health and productivity (e.g., Clougherty, Souza, & Cullen, 2010; Goh, Pfeffer, & Zenios, 2016); however, the results have been mixed. On one hand, recent literature on employee wellness programs and employee-focused corporate social responsibility (CSR) policies suggests that workplace practices aimed at employee well-being can increase employee retention, productivity, and firm performance (Burbano, 2016, 2018; Carnahan et al., 2017; Flammer & Luo, 2017; Gubler, Larkin, & Pierce 2017). On the other hand, some experimental studies have not found tangible effects of wellness policies on worker health and workplace outcomes (e.g., Song & Baicker, 2019). One of the reasons for such contrasting results is that research has shown average effects of wellness policies on firm outcomes but has not explored how this effect varies by firm type. In this paper, we address this deficiency by examining conditions under which wellness policies may be complementary to firms’ other strategic choices. We focus on one of the most important types of corporate wellness policies—the provision of health insurance (e.g., Goh et al., 2016), and ask under what conditions providing health insurance to workers creates strategic value for a firm.

This paper develops a model based on the concept of labor adjustment costs (hereafter LACs). LACs are actual and opportunity costs that employers incur from human capital departures and productivity losses associated with absenteeism, presenteeism, and employee disengagement1 (Penrose, 1959; Lucas, 1967). Some firms may have inherently higher labor adjustment costs due to factors such as reliance on human capital, that is difficult to replace from the external market and firm-specific human capital (Mahoney & Kor 2015; Wang, He, & Mahoney, 2009). Thus, it is important especially for firms with high labor adjustment costs to manage these costs by retaining and keeping their human capital productive. The paper argues that firms with inherently higher LACs are more likely to offer health insurance over firms with lower LACs because health insurance can contribute to increased job satisfaction, feelings of reciprocity, and enhanced employee mental and physical well-being, which reduces adjustment costs associated with employee turnover and productivity.

We propose that improved employee physical and mental well-being and job satisfaction are the main mechanisms through which health insurance can contribute to reducing LACs. Research has shown that employees with health insurance take preventative care and are under less physical and financial burden than employees without health insurance (Finkelstein et al., 2018; Franks, Clancy, & Gold, 1993; Goh et al., 2016; Pfeffer, 2018; Sudano Jr & Baker, 2003; Wilper et al., 2009). Thus, healthier employees are more productive and contribute to firm outcomes (Gubler, Larkin, & Pierce, 2017). Evidence also suggests employee benefits that signal organizational support of employees, such as wellness programs and work-life balance can improve employee job satisfaction and encourage reciprocity from employees (e.g., Eisenberger et al., 2001; Gubler, Larkin, & Pierce, 2017). Thus, we expect that firms with high LACs that offer health insurance will have lower turnover, higher productivity, and greater firm performance than firms with high LACs, but without health insurance.

1 Workers can be absent from work due to medical reasons and disengagement (absenteeism) and become absent while at work due to illnesses and chronic medical and mental conditions (presenteeism).
We focused on the provision of health insurance benefits by small firms in the U.S. primarily for empirical reasons. First, we exploited a large variation in health insurance provisions among small firms. Second, we took advantage of the likelihood that the effects of LACs are more prominent in small firms.

We used data on 15,331 small private firms in the U.S. over the period of 2006-2011. About 22% of the firms provided health insurance in at least one year in our sample period. We measured the difference in LACs of firms by their employee training levels and degree of employee task discretion. We found that firms that have higher LACs are more likely to offer health insurance than firms with lower LACs, and firms with health insurance are more likely to have lower employee turnover and higher employee productivity than firms without health insurance. And, among firms with high LACs, firms with health insurance have higher firm performance than firms without health insurance. To econometrically address the concerns of endogeneity, we employ an instrumental variables (IV) approach and show similar results.

Next, we supplemented our quantitative results with some qualitative evidence to provide support for the mechanism. First, we interviewed small business owners on decisions to offer or not offer health insurance and found evidence of health insurance being a primarily labor-related strategic choice in small firms. Second, we analyzed employee reviews from Glassdoor and found higher reported employee job satisfaction in firms that offered health insurance, consistent with hypothesized mechanisms. All results taken together suggest that health insurance can lower labor adjustment costs and ultimately increase firm performance and competitiveness.

Our paper contributes to the literature that studies the adoption of wellness programs and its effect on engagement and productivity of workers (e.g., Gubler, Larkin, & Pierce, 2017) by identifying conditions under which these programs are strategically important to firms. Firms with higher training needs may also need to invest in employee wellness programs to receive returns on their training investments. We also contribute to the firm-specific human capital literature by examining the role of reducing labor adjustment costs in gaining competitive advantage from firm-specific human capital through workplace policies (Mahoney & Kor, 2015; Wang, He, & Mahoney, 2009). We highlight some conditions under which management of firm-specific human capital can reduce adjustment costs and be beneficial to firms. Further, our paper is the first to look at health insurance provisions from the human capital management perspective and its impact on firm performance. It contributes to the HR literature that examines bundles of “high performance” HR practices, by proposing and providing evidence of a mechanism by which health insurance can increase firm performance.

REFERENCES


Mahoney JT, Kor YY. 2015. Advancing the human capital perspective on value creation by joining capabilities and governance approaches. Academy of Management Perspectives 29(3): 296-308.


How Do Managers Pass Down Inequality? The effect of pay inequality among managers on pay inequality among workers.

Federica De Stefano (Wharton Business School)

Pay inequality within firms has increased over the past decades, accounting for 31% of the overall increase in labor income inequality in the US from 1978 to 2013 (Song et al., 2018). Research suggests that managers are key actors in shaping these pay differences (Bidwell et al., 2013; Castilla, 2011; Cobb, 2016). In particular, managers’ decisions on the allocation of work define differences in workers’ productivity, protection, resources, and pay (Tomaskovic-Devey et al., 2009).

Previous studies indicate that managers’ compensation affects work allocation and inequality among workers. Bandiera et al. (2007) show that when managers are paid for performance rather than a fixed salary they divert work from low- to high-ability workers increasing inequality in workers’ productivity. Cobb (2016) also suggests that attaching managers’ compensation to market performance increases pay inequality among workers. These studies focus on comparing pay for performance to fixed salary but do not examine how pay inequality among managers affects workers. Meanwhile, studies on pay dispersion document that horizontal pay inequality is a powerful predictor of individuals’ responses to pay (Trevor et al., 2012) but deal only marginally with how inequality within one group of employees affects other groups.

This paper investigates the relationship between horizontal pay inequality—that is, pay differences among individuals in the same job (Trevor et al., 2012)—among managers and horizontal pay inequality among workers. I build on the literatures on relational inequality (Tomaskovic-Devey, 2014) and pay dispersion (Trevor et al., 2012) to examine how pay inequality among managers influences the allocation of work hours and, in turn, pay inequality among workers. The distribution of work hours is particularly relevant to understand horizontal pay inequality among workers because it is a major dimension of the allocation of work and rewards among workers performing the same job.

I rely on the evidence that horizontal pay inequality generates equity concerns when it is "unexplained"—that is, it is unrelated to heterogeneity in employees’ performance (Trevor et al., 2012). Drawing from extant studies on how managers react to inequity and uncertainty (Hallier & James, 1997; Marginson & McAuley, 2008), I contend that managers respond to unexplained inequality by focusing on their short-term pay-offs at the expense of workers. To this end, they minimize labor cost and work hours, increasing the pressure on workers to do more with less. While some workers are vulnerable to the erosion of their hours, others can claim more work and protection (Tomaskovic-Devey, 2014). I argue that these differences in workers’ ability to make claims generate inequality in the hours allocated to them (Tomaskovic-Devey et al., 2009). Inequality in hours leads to pay inequality because it creates differences in workers’ productivity and skills, which influence pay differentials (Bandiera et al., 2007).

Building on these arguments, I hypothesize that horizontal pay inequality among managers is negatively associated with the average hours of work allocated to workers but positively associated with the dispersion of those hours. I also hypothesize that horizontal pay inequality among managers is positively associated with horizontal pay inequality among workers. Finally, I examine how the relationship between manager and worker horizontal pay inequality varies with the manager’s position in the earning distribution.

I test my predictions using longitudinal quarterly data from 2007 to 2014 for the Italian units of a leading multinational restaurant and retail chain. Inequality among managers is defined within the regions
In which units are grouped. Inequality among workers is defined within the unit that each manager runs. Tables 1 and 2 summarize my major findings. I find a negative relationship between inequality in unexplained pay among managers and the average hours assigned to workers (Model 1 in Table 1). I also find that pay inequality among managers is positively related to the dispersion of hours: I find a negative relationship with the hours contracted at the bottom of the distribution of hours (Models 2 and 3 in Table 1) but no relationship with those contracted at the top (Models 4 to 6 in Table 1). The results also indicate a positive relationship between inequality in unexplained pay among managers and pay inequality among workers (Model 1 in Table 2). I find that horizontal pay inequality among managers erodes the salaries of workers at the bottom of the earning distribution more than those of workers at the top (Models 2 to 6 in Table 2). I find these effects to be amplified when workers are managed by a manager at the bottom of the managers’ earning distribution.

This study has two major intended contributions. First, it contributes to the research on how organizations generate inequality (Cobb, 2016) by investigating how managers push inequality down to workers. Second, it extends the literature on pay dispersion (Trevor et al., 2012) by examining the effects of horizontal pay inequality outside the group within which pay differences are defined.
REFERENCES


## TABLE 1: The relationship between inequality in manager unexplained pay and work hours. a, b, c

<table>
<thead>
<tr>
<th>VARIABLES</th>
<th>(1)</th>
<th>(2)</th>
<th>(3)</th>
<th>(4)</th>
<th>(5)</th>
<th>(6)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Inequality in manager unexplained pay (t-1)</td>
<td>-0.007***</td>
<td>-0.006**</td>
<td>-0.002***</td>
<td>-0.006</td>
<td>-0.001</td>
<td>-0.001</td>
</tr>
<tr>
<td>Inequality in manager explained pay (t-1)</td>
<td>0.002 (0.004)</td>
<td>-0.005 (0.003)</td>
<td>-0.002 (0.001)</td>
<td>0.003 (0.006)</td>
<td>0.001 (0.001)</td>
<td>0.001 (0.001)</td>
</tr>
<tr>
<td>Log of manager pay (t-1)</td>
<td>0.034*** (0.011)</td>
<td>0.019** (0.007)</td>
<td>0.001*** (0.002)</td>
<td>0.001*** (0.018)</td>
<td>0.002*** (0.018)</td>
<td>0.004 (0.002)</td>
</tr>
<tr>
<td>Worker tenure</td>
<td>0.011*** (0.000)</td>
<td>0.001*** (0.000)</td>
<td>0.001*** (0.000)</td>
<td>0.015*** (0.000)</td>
<td>0.002*** (0.000)</td>
<td>0.002*** (0.000)</td>
</tr>
<tr>
<td>Worker gender</td>
<td>-0.164*** (0.001)</td>
<td>-0.006*** (0.000)</td>
<td>-0.012*** (0.000)</td>
<td>-0.216*** (0.000)</td>
<td>-0.035*** (0.000)</td>
<td>-0.035*** (0.000)</td>
</tr>
<tr>
<td>Permanent worker</td>
<td>0.122*** (0.003)</td>
<td>0.020*** (0.002)</td>
<td>0.014*** (0.001)</td>
<td>0.160*** (0.005)</td>
<td>0.023*** (0.001)</td>
<td>0.023*** (0.001)</td>
</tr>
<tr>
<td>Constant</td>
<td>5.547*** (0.082)</td>
<td>5.407*** (0.048)</td>
<td>5.609*** (0.017)</td>
<td>5.478*** (0.142)</td>
<td>6.149*** (0.020)</td>
<td>6.166*** (0.020)</td>
</tr>
</tbody>
</table>

Unit fixed effects Yes, Yes, Yes, Yes, Yes, Yes
Quarter-Year fixed effects Yes, Yes, Yes, Yes, Yes, Yes
Observations 211,607, 211,607, 211,607, 211,607, 211,607, 211,607
R-squared 0.202, 0.202, 0.202, 0.202, 0.202, 0.202
Number of unit-quarter-year groups 10,123, 10,123, 10,123, 10,123, 10,123, 10,123

a Model 1 estimates a fixed effect regression model for the whole population (Unit of analysis: Worker-Unit-Quarter-Year). Models 2 to 6 estimate recentered influence function (RIF) regressions to examine the effect of Inequality in manager unexplained pay \(t-1\) on Log of work hours by worker, by work hours percentiles (Unit of analysis: Worker-Unit-Quarter-Year).

b Standard errors in parentheses

c *** p<0.001, ** p<0.01, * p<0.05
### TABLE 2: The relationship between inequality in manager unexplained pay and pay inequality among workers, \textsuperscript{a, b, c}

<table>
<thead>
<tr>
<th>VARIABLES</th>
<th>Coefficient of variation of worker pay ( t )</th>
<th>Log of worker pay ( t ) 10\textsuperscript{th} pay percentile</th>
<th>Log of worker pay ( t ) 25\textsuperscript{th} pay percentile</th>
<th>Log of worker pay ( t ) 50\textsuperscript{th} pay percentile</th>
<th>Log of worker pay ( t ) 75\textsuperscript{th} pay percentile</th>
<th>Log of worker pay ( t ) 90\textsuperscript{th} pay percentile</th>
</tr>
</thead>
<tbody>
<tr>
<td>Inequality in manager unexplained pay ( t-1 )</td>
<td>0.002\textsuperscript{*} (0.001)</td>
<td>-0.011\textsuperscript{*} (0.005)</td>
<td>-0.010\textsuperscript{**} (0.004)</td>
<td>-0.013 (0.008)</td>
<td>-0.005\textsuperscript{*} (0.002)</td>
<td>-0.003 (0.004)</td>
</tr>
<tr>
<td>Inequality in manager explained pay ( t-1 )</td>
<td>-0.006\textsuperscript{**} (0.002)</td>
<td>-0.014 (0.010)</td>
<td>-0.006 (0.006)</td>
<td>0.016 (0.015)</td>
<td>0.010\textsuperscript{*} (0.005)</td>
<td>0.032\textsuperscript{***} (0.009)</td>
</tr>
<tr>
<td>Manager tenure ( t )</td>
<td>0.001 (0.001)</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Number of employees in the unit ( t )</td>
<td>-0.001 (0.000)</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Proportion of female employees in the unit ( t )</td>
<td>-0.042 (0.050)</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Unit complexity ( t )</td>
<td>0.001 (0.001)</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Coefficient of variation of workers’ tenure in the unit ( t )</td>
<td>0.020\textsuperscript{***} (0.019)</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Log of manager pay ( t-1 )</td>
<td>0.001 (0.007)</td>
<td>0.099\textsuperscript{***} (0.027)</td>
<td>0.049\textsuperscript{***} (0.015)</td>
<td>0.038 (0.000)</td>
<td>0.013\textsuperscript{***} (0.000)</td>
<td>0.012\textsuperscript{***} (0.000)</td>
</tr>
<tr>
<td>Worker tenure ( t )</td>
<td>0.008\textsuperscript{***} (0.000)</td>
<td>0.010\textsuperscript{***} (0.000)</td>
<td>0.036\textsuperscript{***} (0.000)</td>
<td>0.013\textsuperscript{***} (0.000)</td>
<td>0.013\textsuperscript{***} (0.000)</td>
<td>0.012\textsuperscript{***} (0.000)</td>
</tr>
<tr>
<td>Worker gender ( t )</td>
<td>-0.041\textsuperscript{***} (0.002)</td>
<td>-0.065\textsuperscript{***} (0.002)</td>
<td>-0.460\textsuperscript{***} (0.005)</td>
<td>-0.115\textsuperscript{***} (0.000)</td>
<td>-0.138\textsuperscript{***} (0.002)</td>
<td></td>
</tr>
<tr>
<td>Permanent worker ( t )</td>
<td>0.715\textsuperscript{***} (0.010)</td>
<td>0.316\textsuperscript{***} (0.004)</td>
<td>0.416\textsuperscript{***} (0.009)</td>
<td>0.044\textsuperscript{***} (0.002)</td>
<td>0.033\textsuperscript{***} (0.002)</td>
<td></td>
</tr>
<tr>
<td>Constant</td>
<td>0.196\textsuperscript{*} (0.081)</td>
<td>6.280\textsuperscript{***} (0.215)</td>
<td>7.182\textsuperscript{***} (0.115)</td>
<td>7.258\textsuperscript{***} (0.308)</td>
<td>8.280\textsuperscript{***} (0.104)</td>
<td>8.136\textsuperscript{***} (0.215)</td>
</tr>
</tbody>
</table>

Manager fixed effects
Unit fixed effects
Quarter-Year fixed effects
Observations
R-squared
Number of unit groups
Number of unit-quarter-year groups

\textsuperscript{a} Model 1 estimates a fixed effect regression model for the whole population (Unit of analysis: Unit-Quarter-Year). Models 2 to 6 estimate recentered influence function (RIF) regressions to examine the effect of Inequality in manager unexplained pay \( t-1 \) on Log of worker pay \( t \), by pay percentiles (Unit of analysis: Worker-Unit-Quarter-Year).

\textsuperscript{b} Standard errors in parentheses

\textsuperscript{c} *** p<0.001, ** p<0.01, * p<0.05
As firms are experiencing recruiting difficulty and talent shortage, the use of employee perks to attract, motivate, and retain people is becoming increasingly important to organizational competitiveness (Campbell et al., 2012; Coff, 1997; Coff and Kryscynski, 2011). Consequently, innovating along the human resource dimension (Duberley and Walley, 1995; Ichniowski et al., 1996; Klaas et al., 2010) has become a strategy imperative, especially for the small and new entrepreneurial ventures that rely heavily on human capital (Unger et al., 2011). In fact, entrepreneurial firms are becoming the bellwether in the use of non-conventional benefits and perks. Typically, these firms adopt perks to attract workers to stay at the workplace – examples include free meals, onsite massage, office childcare center, etc. However, another set of popular perks are making it easier for employees to leave the workplace. These perks, such as work-from-home option, flexible hours, and unlimited vacation, are particularly appealing to workers as they endow flexibility and autonomy. Yet, these perks are not immaculate and can be “dicey,” presenting potential costs and risks to firms if they are abused by indolent or disloyal workers.

This paper aims to shed light on the trade-off in the organizational use of dicey perks. I refer to “dicey perks” as non-monetary benefits offered to employees that are risky and that can be potentially abused. Why do firms offer these dicey perks? How can they minimize the risks of unwanted consequences? While some dicey perks have been examined by scholars, such as work-from-home option and flexible hours (Bloom et al., 2015; Mas and Pallais, 2017), unlimited vacation remains unexplored. Despite being new, this perk has gained significant traction — almost 2,000 firms have been identified to offer unlimited vacation to workers. I propose the first study to investigate unlimited vacation both theoretically and empirically. By unveiling how different types of workers respond to unlimited vacation under varying conditions, I discuss how firms can strategically benefit from this dicey perk and how they can incentivize desirable work behavior to maximize the gains.

Motivated by a content analysis of benefits review for about 33,000 firms, I establish a theoretical model to predict how workers with different abilities respond to unlimited vacation both in the recruitment phase and in the subsequent working phase. These predictions are tested in a longitudinal randomized controlled experiment with an online labor market, Amazon Mechanical Turk. Workers were recruited online for a 4-week-long image-counting job with decent pay. I first assigned workers to either a high ability or a low ability treatment. Workers were then either given a chance to choose between an unlimited vacation contract and a capped vacation contract, or randomly assigned to one of the two contracts. I also manipulated whether the workers experienced a strong or a weak firing threat under unlimited vacation when performance expectation could not be met. I observed the contract selection choices of workers as well as their daily decisions about work and vacation. A follow-up survey collected information about workers’ perception of the job.

The experimental findings confirm my theoretical predictions. First, the unlimited vacation contract attracts the more capable candidates to the recruitment pool. Second, unlimited vacation creates complementarity to work that makes people more productive, even controlling for the sorting effect. Survey evidence suggests a difference in endowed employer trust and perceived flexibility associated with the two contracts that may contribute to the productivity gain. Furthermore, a stronger firing threat reduces the likelihood of slacking and nudges workers to produce more. In addition, I find that the majority of the unlimited vacation workers produce extra work outputs out of a career concern; they are also happier than their capped vacation counterparts.
This paper makes a few contributions. First, unlimited vacation suggests a sorting mechanism for nonpecuniary benefits that can be strategically valuable to firms in recruitment (Phillips and Gully, 2015). Second, the human resource management literature has provided evidence that certain HR practices are positively correlated with worker productivity (Becker and Gerhart, 1996; Datta et al., 2005; Koch and McGrath, 1996). The causal results regarding the productivity gains of unlimited vacation offer additional insights to this strand of work in light of more recent innovative perks. Third, this study adds to the strategy and strategic human resource management literature by causally showing the strategic benefits from the use of unlimited vacation with individual-level experimental evidence and shedding light on the potential mechanisms with survey evidence. Fourth, my findings illustrate how dicey perks may present a management dilemma (Coff, 1997) and thus should be accompanied by clear performance expectation and appropriate threat of punishment (Becker, 1968; Lazear, 2000) to mitigate potential agency problems (Eisenhardt, 1989). Fifth, by focusing on a perk originating from and most popular in startup companies, the results have implications for the study of human resource management in entrepreneurship (Andries and Czarnitzki).
Multi-Layered Labor Contracting and Distribution of Power: Evidence from Employment Records for Nonstandard Work

Hye Jin Rho (MIT Sloan)

This paper examines an important yet little-understood development in the industry that dictates the recruitment of nonstandard workers – the rise in the “multi-layered labor contracting” structure in which the recruitment function of nonstandard workers is outsourced to an intermediating organization. The intermediary then selects qualified workers from a group of competing suppliers (i.e. staffing agencies) in a cloud-based technological platform in the form of hyper-subcontracting. For nonstandard workers, this means that it sometimes takes multiple steps (or layers) of contractual relationships, often without their knowledge, to be matched to a work assignment at the firm where they perform tasks. While the phenomenon has become widespread, virtually no research has closely examined this trend, the variation in firms’ use of intermediating organizations, and its potential economic impact on the lead firm and/or the workers seeking employment in nonstandard jobs.

Not only is there a lack of publicly available data that tracks how firms vary in their hiring of nonstandard workers, but previous research on nonstandard work has mostly looked within a triadic (or dyadic) arrangement, whether it be for a single-firm, industry, or skill level job. However, detailed case-based narratives in these studies occasionally allude to more than one pathway through which nontraditional workers and firms find each other, even for the same type of the job. Evans, Kunda, and Barley (2004), for example, identifies two markets for technical contractors, one in which they find work by negotiating directly with the lead firms as independent agents, the other in which they have staffing agencies find work for them. Because these agencies as job-matching brokers have some discretion in the price setting process (see Fernandez-Mateo 2007), the prices agencies charge the firm and pay the workers will fundamentally differ from the prices negotiated between the firm and the workers directly; or from the prices negotiated between three or more actors in a contractual relationship. I make the very first scholarly attempt to examine the link between such multi-layered contracting arrangements and subsequent economic outcomes for both the hiring lead firms and the workers.

Using power-dependence theory, I argue that the lead firm’s discretion to outsource the recruitment function in a technological platform compresses supplier power, which then incentivizes suppliers to transfer the competitive price burden to workers. For the analyses, I use unique and proprietary data from employment records of about a million workers seeking nonstandard work at 49 large firms. To my knowledge, this is the first available data that provides detailed information on how nonstandard workers are hired (or onboarded) to work assignments across multiple large firms in the United States: specifically, a detailed list of suppliers and their types, information on the lead firms that workers get assigned to, assignment characteristics, and their prices. Importantly, the data has information on whether these large firms have outsourced their “contingent workforce management” (CWM) programs to a third-party agency.

Using OLS regression models, I find that an additional contracting layer between the lead firm and the worker is associated with higher returns to the firms and lower returns to the workers. When workers gain bargaining power, however, through a pre-existing firm-worker relationship, the results show that the loss from an additional contracting layer is significantly reduced. The results hold even when controlling for supplier fixed effects to control for unobservable supplier characteristics, such as the likelihood of being a high- or low-road employers. Further, I develop a measure of skill requirements by coding specific skills demanded for each of about 200,000 job descriptions. It may be the case that the effect of additional
contracting layer on prices is driven by heterogeneity in skills demanded when the lead firm hires workers through an intermediary as opposed to internally. The result holds even when controlling for detailed measurement of skill requirements for nonstandard jobs that may instead dictate the price-setting process. Findings from this paper have potential for improving our knowledge of hiring practices in organizations and social structural inequality using the theoretical constructs of power and price-setting. It aids our understanding of how nonstandard workers are hired in today’s labor market and how their wages are set by opening the "black box" of institutional processes which are much more complicated than previously examined.
Subject Belief about Contract Enforceability
Evan Starr (University of Maryland)

Introduction
In the last decade there has been significant academic and policy interest in the examination of frictions that limit the within-industry mobility of human capital, mostly focused on state policies related to covenants not to compete (Marx et al. 2009, Treasury 2016). However, recent research has found that noncompetes are nearly as common in states that do not enforce them as in states that do (Bishara et al. 2015, Starr et al. 2019), raising questions about the validity of the state policy approach in the literature and about what workers know or believe about the law.

Existing research often makes a crucial assumption that agents are informed of their legal environment (Garmaise 2009), even though prior research in law tends to find that – at least in non-work contexts – the use of unenforceable contract terms are viewed as enforceable by individuals. In the work context, however, this might not be true: the stakes are higher, contracts are negotiable, and parties have access to legal counsel. More generally, when a contract may restrict an individual’s ability to make a living, that individual has a strong incentive to understand the enforceability of that contract.

Given the importance of noncompetes, and the disconnect in the prior literature related to the proper assumptions about knowledge of the law, in this study we use detailed, nationally representative survey data and an information experiment on 11,505 labor force participants to examine the following questions: (1) What do workers believe about the enforceability of noncompetes and are those beliefs accurate? (2) How is (endogenous) mis/uninformedness related to mobility outcomes? (3) How does (randomly) informing individuals about the actual policies of their state influence their prospective mobility and entrepreneurial intentions? (4) What is the causal effect of believing that a court will enforce a noncompete on prospective decisions? (5) Why are workers in low enforcing states persistently uninformed?

Our findings are detailed below. To summarize the contribution briefly: This study provides the first evidence on worker knowledge of the enforceability of noncompetes. We find that workers persistently believe their noncompetes are enforceable, even when they aren’t, and that these beliefs matter strongly for their prospective mobility choices. Revisiting the literature on state policies (e.g., Marx et al. 2009), these results imply that prior studies have been missing a crucial part of the story: Even unenforceable noncompetes matter because workers do not know they are unenforceable, and, moreover, we provide evidence that firms appear to actively seek to keep workers misinformed.

Data
To examine what workers know about the enforceability of noncompetes, we surveyed 11,500 workers in 2014. In this study we leverage two novel elements of the survey: (1) Questions asking respondents about their beliefs about noncompete enforceability, and (2) an information experiment which randomly informed respondents of their state law.

---

2 Though also including the inevitable disclosure doctrine (Contigiani et al. 2018), and trade secret protections (Png 2016)
4 Prior work using this data has documented the pervasive use of non-competes, their associations with wages, training, job satisfaction, mobility, and their external effects on the market (Starr et al. 2018, Starr et al. 2019a, Starr et al. 2019b).
What do workers believe about the enforceability of noncompetes?

Figure 1 shows that worker beliefs about the enforceability of noncompetes are uncorrelated with actual enforceability, while Figure 2 shows those in low/no enforceability states are 50 p.p. less likely to correctly estimate enforceability.

How is (endogenous) mis/uninformedness related to mobility outcomes?

[Answer skipped for brevity. See Figure 3.]

How does (randomly) informing individuals about the actual policies of their state influence their prospective mobility and entrepreneurial intentions?

Figure 4 displays the distribution of beliefs about enforceability before and after the information experiment. The experiment appears to have worked as expected: those in the low/no enforceability states strongly shift their beliefs towards zero enforceability, those in the medium enforceability states bunch more in the middle, and in the high enforceability states there is a moderate shift rightward.\(^5\)

The right panel of Figure 5 examines an indicator for whether the noncompete would be a factor in the respondent’s choice to leave for a competitor. Those informed of the law in states that do not enforce noncompetes now report that their noncompete would be less likely to be a factor in their choice to leave.

What is the causal effect of believing that a court will enforce a noncompete on prospective decisions?

The information experiment exogenously changed beliefs about enforceability, and so we can use it as an instrument for (post experiment) beliefs to understand how believing a noncompete is enforceable is causally related to subsequent mobility intentions. Table 3 reports the instrumented results: believing that a noncompete will be enforced increases the chance you perceive your firm will sue you, and the extent to which you will pursue outside options at other firms or on your own.

Why are workers persistently uninformed?

Consistent with the notion that competitors would inform workers about the law, we find that workers who received job offers in the last year from competitors were relatively more accurate in their beliefs than those who did not receive such an offer.\(^6\) We also find that firms in low enforceability states are more likely to encourage misinformation: they are 25 p.p. more likely to remind workers about their non-compete (left panel of Figure 6). Furthermore, reminders appear to raise beliefs of enforceability, regardless of the level of actual enforceability (right panel of Figure 6).

---

\(^5\) The left panel of Figure 5 documents differences in the means between those who got information and those who didn’t according to their enforceability level. As in Figure 4, those in the low enforceability states revise downward their beliefs on average by about 20 percentage points.

\(^6\) We omit these results for the sake of brevity.
Figure 1. Beliefs about Enforceability are Uncorrelated with Actual Enforceability

Figure 2. Beliefs about Noncompete Enforceability and Actual Noncompete Enforceability
Figure 3. Search and Mobility Behavior as a Function of Informedness and Actual Enforceability

Sample includes only affirmed noncompete signers.

Figure 4. Pre-Post Experiment Changes in Beliefs about Enforceability
Figure 5. Information Experiment, Beliefs about Enforceability, and Factor in Leaving

Sample includes only affirmed noncompete signers.

Figure 6. Reminders about Noncompetes and Beliefs about Enforceability

Sample includes only affirmed noncompete signers.
### Table 3. Instrumenting for post-experiment enforceability beliefs.

<table>
<thead>
<tr>
<th>Panel A: Post experiment beliefs about being sued and other prospective decisions</th>
<th>(1)</th>
<th>(2)</th>
<th>(3)</th>
<th>(4)</th>
<th>(5)</th>
<th>(6)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Dependent Variable: Post Experiment</td>
<td>P(Employer would sue over CNC if violated)</td>
<td>1(Current noncompete limits future job option)</td>
<td>1(CNC factor in joining competitor)</td>
<td>1(CNC factor in starting competitor)</td>
<td>1(CNC factor in joining competitor)</td>
<td>1(CNC factor in starting competitor)</td>
</tr>
<tr>
<td>Instrumented Post Experiment P(Enforce)</td>
<td>0.334***</td>
<td>0.004***</td>
<td>0.006***</td>
<td>0.005***</td>
<td>0.005***</td>
<td>0.005***</td>
</tr>
<tr>
<td>Controls</td>
<td>Yes</td>
<td>Yes</td>
<td>Yes</td>
<td>Yes</td>
<td>Yes</td>
<td>Yes</td>
</tr>
<tr>
<td>Pre-Experiment measure of dependent variable</td>
<td>Yes</td>
<td>Yes</td>
<td>Yes</td>
<td>Yes</td>
<td>Yes</td>
<td>Yes</td>
</tr>
<tr>
<td>Mean of Dependent Variable</td>
<td>38.9</td>
<td>0.233</td>
<td>0.415</td>
<td>0.523</td>
<td>0.523</td>
<td>0.523</td>
</tr>
<tr>
<td>% Δ in DV from 50 pp increase in P(Enforce)</td>
<td>42.93%</td>
<td>85.84%</td>
<td>72.29%</td>
<td>47.80%</td>
<td>47.80%</td>
<td>47.80%</td>
</tr>
</tbody>
</table>

### Panel B: Suppose that at your current job you receive an offer to perform your same duties in a comparable, competing company. How important are the following factors in determining whether or not you decide to move to the comparable, competing company? (7 Extremely important to 1 Not at all important)

<table>
<thead>
<tr>
<th>Dependent Variable: Post Experiment</th>
<th>Importance of &quot;The fact that I signed and agreed to the CNC&quot;</th>
<th>Importance of &quot;The employer would take legal action to enforce CNC&quot;</th>
<th>Importance of &quot;The chance that I would have an opportunity to do more exciting work&quot;</th>
<th>Importance of &quot;The chance that I would receive compensation or other benefits&quot;</th>
<th>Importance of &quot;The chance that the new job and other lifestyle benefits&quot;</th>
</tr>
</thead>
<tbody>
<tr>
<td>Instrumented Post Experiment P(Enforce)</td>
<td>0.020***</td>
<td>0.015***</td>
<td>0.030***</td>
<td>-0.008***</td>
<td>-0.017***</td>
</tr>
<tr>
<td>Controls</td>
<td>Yes</td>
<td>Yes</td>
<td>Yes</td>
<td>Yes</td>
<td>Yes</td>
</tr>
<tr>
<td>Pre-Experiment measure of dependent variable</td>
<td>Yes</td>
<td>Yes</td>
<td>Yes</td>
<td>Yes</td>
<td>Yes</td>
</tr>
<tr>
<td>Mean of Dependent Variable</td>
<td>4.45</td>
<td>4.52</td>
<td>4.54</td>
<td>1.04</td>
<td>1.57</td>
</tr>
<tr>
<td>% Δ in DV from 50 pp increase in P(Enforce)</td>
<td>22.47%</td>
<td>16.59%</td>
<td>33.04%</td>
<td>-38.46%</td>
<td>-54.14%</td>
</tr>
</tbody>
</table>

*** p<0.01, ** p<0.05, * p<0.1. Robust standard errors in parentheses, clustered at the state level. Sample includes only noncompete signers. All models include the main effects of the pre-experiment measure of the particular dependent variable, which are all measured a second time after the experiment (both or those who did and did not receive the information). The instrument for post experiment beliefs is a three-way interaction of pre-experiment beliefs about enforceability, being in a no/low, medium, or high enforceability state, and whether they randomly received information. Controls include the pre-experiment beliefs about enforceability, indicators for enforceability (no/low, medium, high), indicators for the way the worker is paid, a third degree polynomial in age, hours worked per week, weeks worked per year, the interaction of hours and weeks worked, gender, class of the worker (non-profit, for-profit), indicators for highest educational attainment, multi-unit firm, firm size, and the log of the number of firms in the worker's industry-county.
References


The question of how workers express their dissatisfaction with organizations – whether due to organizational decline, scandals or perceived exploitation – is an important one. In Hirschman’s (1970) landmark theory, exit and voice are positioned as alternative responses to discontent. This original framework implies that exit and voice are substitutes – that is, when exit options become more feasible, voice (i.e., actively expressing discontent) decreases. In this paper, we revisit this framework and provide empirical evidence on voice in the presence of alternative options. We argue – in line with later writing by Hirschman – that under some circumstances, exit and voice might be complements instead of substitutes. In particular, we contend that when the possibility for organizational retribution is high, exit and voice are both likely to increase in response to alternative options.

We empirically examine this question in the setting of the gig economy. In this context, we introduce the idea of partial exit: the idea that workers need not leave a platform entirely when they are dissatisfied, but rather partially shift their labor allocation to alternative platforms. We formulate two key predictions for how market share gains from an alternative platform will affect worker behavior. First, the emergence of the alternative platform reduces the threat of impactful retribution, increasing workers’ likelihood of exercising voice. Second, the prominence of the alternative platform increases search and coordination costs for workers, requiring they spend more effort monitoring and comparing platforms as they choose to allocate work between them.

In testing these predictions, we look to the ride-sharing market, analyzing over 600,000 posts from more than 15,000 drivers on uberpeople.net, the largest online forum for ride-sharing drivers. This highly active forum functions like a digital version of the proverbial water cooler, acting both as a space for socialization and knowledge-sharing. Exploiting the uneven gains in market share made by Lyft across 59 cities in the U.S. from 2014 to 2018, we examine how an increased Lyft presence in a given city affects the online behavior of the drivers based there. We show that drivers utilize the forum more as Lyft gains prominence in their city: a 10 percent increase in Lyft market share is associated with 3.6 more posts per driver in the subsequent month, an increase of more than 25 percent over the mean. We show that one of the areas of the forum in which this additional posting is concentrated is advocacy – a specific subforum for labor organizing – providing evidence that opportunity for partial exit is associated with greater voice. We also demonstrate that areas of the forum dedicated to coordination and monitoring see greater activity as Lyft gains market share. Using topic modeling, we provide descriptive evidence of the semantic subjects within subforums that see increased discussion as a result of higher Lyft share, demonstrating with greater precision that the increased activity is a function of knowledge sharing on how to compare the different platforms and their policies.

This paper makes contributions to several different literatures. First, it contributes to the literature on how workers express their dissatisfaction with organizations, particularly the exit-voice theory and its extensions. Our contribution suggests a theoretical framework for understanding when exit and voice will function as complements, rather than substitutes, in the presence of alternative options. Second, we contribute to the growing body of work on the gig economy. This context is growing in relevance – is estimated that about a third of U.S. workers have an alternative work arrangement as their primary job (Gallup 2018) – and research interest in the setting is growing in tandem. However, as noted by Capelli and Keller (2013), most management and organization theories are still based on the presumption of full-time traditional employment. In response to that call, we revisit a classic theory of the organization in light...
of features of the new economy. Finally, we contribute to the literature on online communities, and demonstrate its usefulness for researchers aiming to gain a glimpse into workers’ conversations. With the help of text analysis tools, we are able to understand better how workers communicate with one another, and allows us to in particular to study the extent and content of workers' use of voice. Our results show that the “digital water cooler” can serve as a venue not only for knowledge sharing and socialization (Hwang et al 2015, Faraj et al 2011), but for labor organization and advocacy as well.
References


Passing On Power: Who Inherits Clients of Retiring Professional Partners?
Andrew von Nordenflycht (Simon Fraser University), Forest Briscoe (Penn State University) and Heidi Gardner (Harvard University)

One of the distinctive organizational forms in professional services is the large professional partnership (Greenwood et al 1990; Brock, Powell and Hinings 1999). Professional partners typically enjoy power, status and high income. Not surprisingly, much research on professional careers, including that which focuses on demographic inequality, studies factors that predict junior professionals probability of making partner (Greenwood et al. 2005; Kay and Gorman 2012).

But what happens after making partner? The stylized model of the professional partnership is that it is a group of peers (Lorsch and Tierney 2002), a “company of equals” (Nelson 1988). However, closer inspection reveals that partnership ranks are stratified (Wilkins 1999). But while there is growing research on the cross-firm mobility of partners (e.g., Sherer and Lee 2002; Rider and Tan 2014; Rider and Negro 2015), there is precious little research on partner careers within a given firm. Presumably, demographic factors will play familiar roles in cross-partner inequality, but does partner success come from different sources that make those factors more or less influential?

A primary source of partner power is control over client relationships (Blair-Loy 2001). Case studies indicate partner compensation is often strongly influenced by the revenue generated by clients the partner has brings to the firm or whose work the partner oversees (Altman Weil 2000; Gabarro and Burtis 2006; Regan 2004). And maintaining a client’s business is often highly contingent on a specific partner’s continued presence at the firm. For instance, Somaya et al (2008) and Briscoe and Rogan (2015) show that law firms’ performance suffers when partners depart to other firms. This threat of leaving gives partners with more client relationships more power.

How, then, do partners come to acquire client relationships? Briscoe and von Nordenflycht (2014) theorize two social networking strategies that partners might choose to obtain client relationships: “inheritance”, in which junior partners build relationships with senior partners to be in position to be “bequethed” the client when the senior partner retires; and “rainmaking”, in which partners seek to obtain clients new to the firm. Interestingly, analyzing records of a large law firm, they argue that the payoff to the inheritance strategy differs for male vs. female partners: more time spent working with senior partners predicts greater future client revenue for men, but lower future client revenue for women.

This study analyzes more closely the client inheritance process. Our question is what factors predict which junior partner will inherit the client of a senior partner. In particular, we seek to estimate the effects of homophily: the extent to which the focal partner and the “bequething” partner share similar demographic and background characteristics. To what extent does homophily explain inheritance, relative to the amount of time junior partners invest in working with bequethers’ clients?

SAMPLE AND METHOD
We use internal timekeeping records of two large US law firms. The sample includes 643 partners from 2005-2012 for one firm, and 839 partners from 2002-2017 for the other. The records indicate the hours each partner worked on each project, and which partner was responsible for the relationship with the project’s client (i.e., who “owned” the client). This allows us to identify which partners worked with which
other partners and whether the responsibility for clients passes from one partner to another. The records also provide a range of demographic and background information on each partner.

We identify the “contenders” for inheriting a client as partners that billed hours to any client owned by a partner 55 years or older. Our unit of analysis is the combination of a contender and a client whose ownership passed from a 55+ partner to one of the contenders (whether or not it was the focal contender). Our dependent variable is an indicator set to 1 if the contender inherited the client, 0 otherwise. Table 1 describes the independent variables.

We include preliminary results using one of the firms. The analysis is based on 102 client accounts whose ownership passed from one partner to another (and where there were multiple contenders). These inherited clients yield 6,450 contender-client observations.

RESULTS

Table 2 reports results from two fixed effects logit models. The first measures the effect of gender simply by including the gender of the contender. The second measures gender homophily more directly with dummies for each combination bequether and contender gender (with male-male excluded). The model includes fixed effects for each bequether.

Not surprisingly, the more of the client’s work a contender does, the more likely he/she is to inherit it. The homophily factors show mixed results. Age difference has no correlation with the likelihood of inheriting. But law school has a positive correlation with strong statistical significance. Female contenders have a negative coefficient, but there is a 23% chance it is not different from zero. In model 2, none of the gender combos reach a 10% level of statistical significance. Intriguingly, though, the coefficients are not consistent with homophily, indicating that female bequethers are more likely to pass clients to men and less likely to pass to women.

On-going analyses will add results from the second firm (where we have identified over 1,900 clients that change ownership), add network-position variables, and more deeply analyze the interactions between work investment, client characteristics, and contender demographics.

CONCLUSION

Preliminary analyses indicate the possibility of homophily-driven inheritance, over and above the relationship-building investments made by junior partners.

By focusing on the inter-generational transfer of client relationships, we seek to enhance understanding of how organizational practices contribute to (or mitigate) inequality at the highest echelons of the labor market (Kay and Gorman 2012; Fernandez and Sosa 2005; Briscoe and Konrad 2006; Bidwell, et al., 2013).
Table 1: Independent Variables

<table>
<thead>
<tr>
<th>Variable</th>
<th>Description</th>
</tr>
</thead>
<tbody>
<tr>
<td>contenders</td>
<td>number of contenders for this client account</td>
</tr>
<tr>
<td>worked for client?</td>
<td>indicator = 1 if contender worked on any projects for this client</td>
</tr>
<tr>
<td>% of client hours</td>
<td>contender’s hours billed to this client as % of total hours billed to this client (from beginning of sample)</td>
</tr>
<tr>
<td>same practice</td>
<td>contender is in same practice area as “bequether”</td>
</tr>
<tr>
<td>age difference</td>
<td>age difference between contender and bequether</td>
</tr>
<tr>
<td>same school</td>
<td>contender went to same law school as bequether</td>
</tr>
<tr>
<td>female contender</td>
<td>indicator = 1 if contender is female</td>
</tr>
<tr>
<td>male-female</td>
<td>=1 if bequether is male and contender is female</td>
</tr>
<tr>
<td>female-male</td>
<td>=1 if bequether is female and contender is male</td>
</tr>
<tr>
<td>female-female</td>
<td>=1 if bequether is female and contender is female</td>
</tr>
<tr>
<td>female contender X % of client hours</td>
<td>interaction of female with contender’s share of hours billed to the client</td>
</tr>
</tbody>
</table>
Table 2: Conditional Fixed Effect Logit Models of Client Inheritance on Contender Characteristics

<table>
<thead>
<tr>
<th>DV unit</th>
<th>Inherited Client? contender-client</th>
<th>xtlogit, fe Model 1</th>
<th>Model 2</th>
</tr>
</thead>
<tbody>
<tr>
<td># contenders</td>
<td>(0.01) 0.000</td>
<td>(0.01) 0.000</td>
<td></td>
</tr>
<tr>
<td>worked for client?</td>
<td>1.47 0.000</td>
<td>1.47 0.000</td>
<td></td>
</tr>
<tr>
<td>% of client hours</td>
<td>3.04 0.000</td>
<td>3.04 0.000</td>
<td></td>
</tr>
<tr>
<td>same practice</td>
<td>0.79 0.000</td>
<td>0.78 0.000</td>
<td></td>
</tr>
<tr>
<td>age difference</td>
<td>(0.003) 0.793</td>
<td>(0.005) 0.700</td>
<td></td>
</tr>
<tr>
<td>same school</td>
<td>1.260 0.001</td>
<td>1.290 0.000</td>
<td></td>
</tr>
<tr>
<td>female contender</td>
<td>(0.52) 0.228</td>
<td></td>
<td></td>
</tr>
<tr>
<td>male-female</td>
<td>(0.46) 0.306</td>
<td></td>
<td></td>
</tr>
<tr>
<td>female-male</td>
<td>0.25 0.273</td>
<td></td>
<td></td>
</tr>
<tr>
<td>female-female</td>
<td>(0.68) 0.221</td>
<td></td>
<td></td>
</tr>
<tr>
<td>female_contender X % of client hours</td>
<td>0.43 0.491</td>
<td>0.45 0.466</td>
<td></td>
</tr>
</tbody>
</table>

| n | 6,586 | 6,586 |
| clusters | 108 | 108 |
| Psuedo R2 | 0.33 | 0.34 |

Notes: Figures to right of coefficient estimates are probability that coefficient is different from zero.
References


Individuals’ Direct and Indirect Contributions in Organizations: Evidence from Temporary Absences of Physicians
Carlos Inoue (University of Toronto)

Abstract
What drives organizational performance is one of the most enduring and important questions for organizational scholars (Taylor 1911; Weber 1978; Scott and Davis 2007). Extant research has often underlined the role of organizational factors, including how organizational structures (Thompson, 1967), routines (Nelson and Winter, 1982), capabilities (Teece, Pisano, and Shuen, 1997), and resources (Barney, 1991) shape the performance of firms. These perspectives highlight that organizational, rather than individual, attributes matter considerably for firm performance. But recently, Mollick (2012) has shown that, even relative to organizational factors, individuals do matter a great deal for firm performance. This is an important finding, but the issues of how and under what conditions individuals matter remains an open question.

This study addresses this question by making a distinction between an individual’s direct contributions to organizational performance and their indirect contributions through enhancing coworkers’ performance. To do so, I consider how temporary absences of highly productive individuals affect both the organizational performance and the individual performance of their coworkers. I propose that the temporary absence of these individuals negatively affects organizational performance due to both individual sorting—differences in individuals’ own performance—and peer effects—differences in the influence individuals have on the performance of peers. While both individual sorting and peer effects influence organizational performance, only the latter affects the individual performance of coworkers.

I test these predictions using data on physicians treating patients with ischemic heart disease in several hospitals in Brazil. Ischemic heart disease, of which heart attack is the primary manifestation, is the leading cause of death worldwide. The data include over 16,000 physicians treating more than 1.4 million patients across 237 hospitals between 2008 and 2017. I define highly productive physicians based on the number of patients treated within hospitals, identifying 279 high-volume physicians that together treated close to 400,000 patients over the period above. The empirical analysis explores how temporary absences of these high-volume physicians affect the performance of their organizations and their peers. The primary performance outcome in this study follows a well-established performance outcome for hospitals and physicians: whether a patient lives or dies.

The empirical strategy uses a difference-in-differences framework to examine the effect of temporary absences of high-volume physicians on both within-hospital and within-physician patient mortality. The identifying assumption behind this approach is that the only reason for changing outcomes in hospitals that experience the absence of a high-volume physician, relative to other similar hospitals, is the absence itself. Although I am able to rule out concerns about permanent differences between hospitals through the use of hospital fixed effects, there are two potential concerns with such approach. The first is that there are underlying trends in hospital outcomes that are concurrent (or even determining) the absence of a physician. For example, deteriorating conditions in a hospital may determine both physician absence and worsening outcomes. I addressed this concern by investigating the dynamics in outcomes around the absences and found no evidence of differential trends both before and after the absences. The second concern is that the absence of a high-volume physician may change the composition of patients in the hospital, leading to changes in outcomes through composition bias. For example, if the absence of a high-volume physician leads to admissions of sicker patients, then the absence would be associated with worse
outcomes but not due to changes in treatment. However, I found little evidence that these absences were correlated with changes in patient demographics or morbidity.

Across a number of specifications, the absence of a high-volume physician increases in-hospital patient mortality by 0.75 percentage points (a 17 percent increase) relative to similar hospitals that do not experience the absence of a high-volume physician. At the same time, the use of percutaneous coronary interventions (PCI)—associated with the implant of coronary stents—decreases about 6.4 percentage points (a 15 percent reduction). Within-physician estimates show that patient mortality is 0.3 percentage points higher during the absence of these physicians, suggesting that peer effects account for 40 percent of the deterioration in performance. The increase in patient mortality is weaker in hospitals where remaining physicians use PCI more intensively. One standard deviation increase in the average PCI intensity of non-absent physicians totally offsets the effect on patient mortality. These findings suggest that highly productive individuals have sizeable influence on the performance of organizations. Whereas Mollick (2012) has demonstrated that individuals matter far more for organizational performance than it was commonly assumed, this study shows that individuals affect organizational performance, to a large extent, through peer effects. So, while individuals clearly matter for firm performance and their impact is non-trivial even relative to organizational factors, the effect of individuals itself is profoundly social.
Variety is the Spice of Hiring: The Effect of Internal-External Candidate Pool Diversity on Post-Hire Performance and Turnover

Kathryn Dlugos (Cornell University)

Firms increasingly recognize the value associated with internal hiring, which occurs when an open job is filled by a current employee (Keller, 2018). Internal hires initially outperform external hires and are less likely to subsequently exit the firm (Bidwell, 2011). The additional probability of motivational spillovers (Bidwell & Keller, 2014) and knowledge transfer (Argote & Ingram, 2000) among current employees has led firms to prioritize internal hiring. However, fully capturing these benefits requires firms to find complementary person-job matches within the firm, which can be difficult. In fact, recent data indicate that nearly 40% of internal moves made by high-potential employees end in failure (Martin & Schmidt, 2010). This suggests there is much to be gained by understanding the challenges associated with internal hiring and how firms overcome them.

The challenges associated with internal hiring stem, in part, from information asymmetries. Internal hires often outperform external hires because information asymmetries are reduced within the firm—hiring managers have more information about internal candidates than external candidates and internal candidates have more information about internal opportunities than external opportunities. Yet even within the firm, the information available to both parties remains incomplete. While a hiring manager may have knowledge about an internal candidate’s performance in a previous job, they lack complete information about their future performance in a new job. Similarly, while internal candidates have firm-specific knowledge that may aid them when entering a new internal job, they lack complete information about what skills and responsibilities are required of the job. These information asymmetries are fueled by continual organizational restructurings and changing job requirements that prevent hiring managers from relying solely on candidates’ previous experiences (Cascio & Aguinis, 2008) and prevent internal candidates from relying on posted job descriptions (Johns, 2012).

Scholars have primarily sought to improve hiring outcomes by increasing the amount of information to hiring managers about potential candidates (Keller, 2018) and the amount of information to potential candidates about open jobs (Breauh, 2013). Following work that explores how the demographic composition of a candidate pool shapes who is ultimately hired for a job (Fernandez & Campero, 2017; Fernandez & Mors, 2008), I instead examine how characteristics of the candidate pool as a whole, rather than those of individual candidates and individual jobs, influence post-hire outcomes. Specifically, I develop theory around information asymmetries to argue that heterogeneous candidate pools (i.e., candidate pools with internal and external candidates) provide information to both hiring managers and internal hires that influence the quality of the match, measured by subsequent performance ratings and turnover. First, I posit that heterogeneous pools allow hiring managers to benchmark internal candidates against external candidates, thereby focusing their attention on the relevant information they possess of internal candidates’ skills and abilities required for the job. Doing so enables them to select better-performing internal hires than they would from pools with only internal candidates. However, I also posit that heterogeneous pools provide information to internal candidates that they are externally marketable; in competing with and being hired over external candidates, internal candidates are likely to believe they can be hired elsewhere and will therefore be more likely to subsequently exit the firm than those internal hires from pools with only internal candidates.

I find support for these arguments using data on over 2,000 internal hires from a large health services organization between 2013 and 2017. In addition to annual personnel records, this dataset details
every internal and external application submitted during the 5-year period, including information on how far each applicant progressed through the hiring process and which applicant was selected. Using logistic regression, I find that internal hires from heterogeneous interview pools are 1.43 times more likely to be rated a top performer in the following year than internal hires from pools with only internal candidates. However, internal hires from heterogeneous interview pools are also 1.99 times more likely to exit the firm in the following year than internal hires from pools with only internal candidates.

This study offers several contributions. First, the theory suggests that candidate pools themselves are an additional source of information that enables hiring managers and potential candidates to evaluate the quality of a potential match. Second, the theory and findings together support the argument that this information influences the post-hire performance and turnover of internal hires. This extends research examining how the demographic characteristics of candidate pools influence who is selected (e.g., Fernandez & Mors, 2008) and complements recent work exploring how different approaches to internal hiring provide different information to hiring managers that influences subsequent employment outcomes (i.e., Keller, 2018). Finally, the findings suggest heterogeneous interview pools are a double-edged sword for organizations; hiring managers may select higher-performing internal candidates, but those internal hires may be more likely to subsequently exit the firm by virtue of being exposed to the external market.

References


A significant focus of labor market researchers has been on analyzing the factors that affect individual career attainment, such as getting an initial job and career mobility. Given that the majority of individuals spend their entire career as wage employees, researchers have largely focused on the organizational factors that affect career outcomes within and between established firms (e.g., Barnett, Baron, and Stuart 2000; Baron and Bielby 1980; Castilla 2008; Ferguson and Hasan 2013; Liu, Srivastava, and Stuart 2015; Rider and Negro 2015). As entrepreneurship became increasingly common as a career choice, with a significant number of individuals being a founder at some point in their career (Buchanan 2015), scholars began to consider the role of entrepreneurship in the career mobility and attainment process. Specifically, the focus of this research is on the transition from wage employment to entrepreneurship (e.g., Azoulay, Liu, and Stuart 2017; Campbell, Kryscynski, and Olson 2017; Carnahan, Agarwal, and Campbell 2012; Chatterji, Figueiredo Jr, and Rawley 2016; Kacperczyk and Younkin 2017; Sørensen and Sharkey 2014).

While most individuals start their career as wage employees at established firms, a number of individuals instead choose to found a venture early in their career. For example, there were approximately 106,000 founders who were 23 years old or younger in the U.S. between 2007 and 2014 (Azoulay et al. 2018). There is reason to believe this number will continue to grow given the significant increase in entrepreneurship education and programs on college campuses across the U.S. The Kauffman Foundation reports that the number of formal majors, minors, and certificates at U.S. universities has increased 5 times from 100 in 1975 to over 500 in 2006; the number of courses in entrepreneurship has grown 20 times from 250 in 1985 to over 5,000 in 2008; the number of college freshmen who aspire to become a founder has increased from 1.5 percent in 1975 to 3.3 percent in 2008; and one-third of incubators are hosted at universities (Kauffman Foundation 2013). However, many of these founders will not remain founders for long.

Within five years of starting their venture, the majority will transition from being founders to being employees at established firms (Dillon and Stanton 2017; Hyttinen and Ilmakunnas 2007). Although research has provided important evidence of how subsequent earnings are affected by entrepreneurial experience, being a founder or former employee of a new venture (Campbell 2013; Luzzi and Sasson 2016), we still lack knowledge on how founder experience is perceived and thus evaluated by firms during the hiring process—an important stage for understanding labor market outcomes. How do these founders fare, relative to if they started their career in wage employment, when they attempt to enter the labor market?

In this paper, we build towards a more comprehensive understanding of the role of entrepreneurship on the career attainment process by theorizing about the effect of founder experience on entry into wage employment, focusing on the first step of the hiring process: getting an interview. The effect of founder experience on the hiring process is rather unclear. On the one hand, we posit that founder experience offers potential benefits that may advantage founders relative to non-founders. Evidence suggests that founders are more likely to possess certain valuable traits, such as being more open to new experiences and having higher self-efficacy in innovation than non-founders (see Kerr, Kerr, and Xu 2018, for a review of personality traits of entrepreneurs). Moreover, the fact that new ventures are often resource constrained (Aldrich and Ruef 2006) forces founders to develop a wide array of other key skills, improving their overall stock of human capital. On the other hand, we posit that founder experience poses potential drawbacks that may disadvantage founders relative to non-founders in the hiring process. A job applicant’s previous
employer signals important information about the applicant’s ability and quality (Bidwell et al. 2014; Phillips 2001); thus, founder experience may lead to uncertainty around the applicant’s quality. Individuals who pursued entrepreneurship may also be seen as “misfits” (Åstebro, Chen, and Thompson 2011); for example, they may not like to be managed (Hamilton 2000). Founder experience may thus lead to uncertainty around the applicant’s ability to fit into and remain committed to an established company as a wage employee (Chatman 1991; Galperin et al. 2019; Goldberg et al. 2016; O’Reilly III, Chatman, and Caldwell 1991; Rivera 2012). Additionally, we theorize how the effect of founder experience is heterogeneous with regards to venture outcomes—a founder of a failed venture versus a more successful venture.

To investigate this question, we conducted a field experiment using an audit-study design, in which we applied to real job openings with fictitious job applications over a 28-day period towards the end of 2018. Specifically, we created three identical job-applicant profiles, varying only their post-undergraduate-degree work experience: wage employee at an established firm, founder of a venture that failed, and founder of a venture that succeeded. Furthermore, we varied the applicant’s gender, resulting in a $3 \times 2$ (founder experience x gender) between-subjects design. Using these six profiles, we randomly applied to 2,400 real full-time entry-level software engineering positions across six metropolitan areas in the U.S. Our main outcome of interest is the number of requests each profile received for an initial job interview from the firms we applied to, in other words, a callback. We also supplemented these data with data on the characteristics of the hiring firms. Beyond offering a causal interpretation of our results, the use of this methodology helps mitigate concerns over selection and generalizability present in observational studies. Lastly, we conducted seven interviews with technical recruiters and hiring managers to help provide further evidence of our proposed mechanisms.

The results of this study highlight that starting one’s career as a founder, on average, leads to fewer callbacks relative to starting one’s career as a wage employee. Furthermore, these outcomes vary based on the nature of that founder’s experience: founders of failed ventures received a greater number of callbacks than founders of successful ventures. Our interview data confirm our posited mechanisms driving these results. For failed founders, the hiring firm’s concerns relate to the founder’s quality, whereas for successful founders, the hiring firm’s concerns relate to the founder’s ability to fit into and remain committed to an established firm. We further unpack our main result by focusing on three sources of heterogeneity: applicant gender, firm age, and job location.
In recent years, diversity in the workplace has garnered increasing attention from academics, employers, workers, investors, regulators, and the general public alike. This is especially true in the technology sector, where firms have come under heavy public and regulatory scrutiny for diversity issues. In 2016, for example, the U.S Equal Employment Opportunity Commission (EEOC) published a special report on diversity in the tech industry and Silicon Valley, identifying “concerning trends” about underrepresentation of minorities and women (EEOC 2016).

In the wake of this, many tech companies seem to signal their commitment to diversity by hiring diversity and inclusion officers, releasing transparency reports, and establishing diversity goals. Despite these efforts, underrepresentation of women, Black, and Hispanic populations continue to persist in tech. Literature in economics, psychology, sociology, and management has addressed why this may be - attributing to various factors, such as preferences (Ceci and Williams 2011; Su et al. 2009), pipeline (Alper 1993; Xie et al. 2015), discrimination, and other environmental and social factors (Ceci and Williams 2007; Diekman et al. 2010; Wang and Degol 2017). A large portion of this literature examines how hiring discrimination in particular contributes to gender and racial segregation across jobs, with a large body of work documenting discrimination against racial minorities (Quillian et al. 2017), men in female-dominated occupations and women in male-dominated occupations (Azmat and Petrongolo 2014; Booth and Leigh 2010; Campero and Fernandez 2018; Riach and Rich 2006; Leung and Koppman 2018).

Various theories have tried to explain possible mechanisms that lead to discrimination. From a microeconomic perspective, hiring managers who imperfectly observe an applicant’s quality may resort to statistical discrimination, i.e. discrimination based on group-level proxies (Kenneth 1973; Phelps 1972). Even in cases where quality can be reasonably inferred, managers may discriminate based on taste. Finally, in firms with diversity goals, managers may be incentivized to align with such goals, potentially leading to discrimination (Leslie et al. 2017).

From an institutional perspective, firms may be incentivized to alter or set goals for their workforce composition for strategic reasons. For example, firms may set such goals to increase team productivity and performance (Cox 1994; Herring 2009; Jehn and Bezrukova 2004; Richard 2000). Another such incentive may be to signal to investors (Wright et al. 1995; Zhang 2018).

Compared to other industries, tech, and Silicon Valley in particular, is different in at least two crucial ways. The applicant pool is predominantly comprised of male, White, and Asian applicants (59% male, 52% white, 36% Asian). Secondly, despite a homogeneous applicant pool, many tech companies are under pressure to increase the diversity of their workforce. Given these opposing dynamics in play, it is unclear how they affect the hiring outcomes of different demographic groups, motivating our study.

To address our research question, we leverage two large-scale proprietary datasets: 1. Applicant Tracking System (ATS) data of 8 Silicon Valley tech firms 2. A dataset of 300 million LinkedIn profiles. The first dataset is aggregated client ATS data provided by an HR analytics firm. To preserve anonymity, our data contains a random subset of clients. In total, the aggregated dataset contains 928k applications across 6,113 job openings spanning 8 years from 2011 to 2018. The available data points include: demographics and resume of each applicant; date, status, and outcome of each application; job title, job description, and business unit of each job opening.
The second dataset is a snapshot of 300 million public LinkedIn profiles as of 2018. We join the ATS dataset with the LinkedIn dataset by joining on LinkedIn profile URL if found in the application. Joining the LinkedIn data allows us to control for additional variables that cannot be easily parsed from the resume text. We were able to match 65% of the ATS applicants with their LinkedIn profiles, and roughly half of these profiles had all the data fields filled out.

In our preliminary analysis, we employ a reduced-form model with a holistic set of applicant and job controls including skills, experience, employment history, education, field of study, and university ranking. Preliminary results show that men are 6.7% less likely to receive a callback, 11.7% less likely to receive an interview, and 19% less likely to receive an offer compared to women. Compared to White applicants, Asian applicants are 4.1%, 18.7%, and 13% less likely to receive a callback, offer, and interview respectively; Hispanic applicants are 6.6%, and 10.4% less likely to receive a callback, and interview respectively; Black applicants are 11.8% less likely to receive a callback. Black females have the largest outcome gap compared to any other group, with probability of callback 14% less than White males. Our findings further suggest that companies are trying to increase company-level diversity through gender, but not necessarily through race.
Missing Women in Tech: The Labor Market for Highly Skilled Software Engineers
Raviv Murciano-Goroff (NYU Stern)

One of the most frequently discussed questions regarding technology companies is why their workforces are persistently gender imbalanced. Despite concerted efforts, many tech companies have been unable to increase the representation of women among their engineering staff. The gender imbalance in tech is often attributed to factors on both the labor supply and labor demand sides (Fernandez and Campero 2017). Determining what can be done to improve diversity in recruiting and hiring at tech firms requires answering two questions: 1) do gender differences in the behaviors of job seekers exist, and 2) do recruiters adjust based on such differences in ways that could increase the diversity of the job applicant pool?

This paper examines the initial screening and recruiting of candidates for software engineering positions. Using unique data from a large online recruiting platform, I investigate if there are gender differences in the decisions of job seekers regarding which technical skills to advertise to potential employers. On the hiring and recruiting platform studied, job seekers post digital resumes with a list of skills they feel proficient in. For a subsample of those candidates, I am able to find actual previous computer code they created and uploaded online. Thus, I am able to compare the programming skills individuals claim proficiency in with some of their actual previous coding work. This comparison enables me to quantify the extent of gender differences in the advertising of programming abilities conditional on measures of candidates' actual previous coding work.

In addition, recruiters from major tech companies subscribe to this platform in order to find and contact potential hires. In my dataset, I observe which candidates on the platform recruiters expressed interest in contacting. I can therefore examine if the self-reporting of programming languages predicts similar or different probabilities of recruiters showing interest in male and female candidates. Furthermore, I can test if recruiters adjust to gender differences in the propensity of candidates to self-report their known programming skills.

I find three main empirical results. First, among all of the information recruiters receive from candidates about their background, tech recruiters are most responsive to the technical skills that individuals self-report on their digital profile. Even when recruiters can see objective evidence that an individual has previous coding experience in a programming language, individuals who also self-report knowing that programming language, are predicted to be approximately 30% more likely to be recruited. The predicted benefits of self-reporting are more limited, however, for those with higher levels of experience in a programming language. Second, female programmers are 9.10% less likely to self-report knowing programming languages that they have experience in than their male counterparts. Surprisingly, this lower propensity to self-report knowledge of a programming language is also apparent when controlling for the usage of one's code by other programmers, a measure of external validation of one's programming skills. Third, recruiters do not adjust for gender differences in the self-reporting of skills. In particular, I do not find evidence that recruiters are more inclined toward recruiting female candidates who self-report knowing a programming language than male candidates with similar profile information shown on this platform.

This paper contributes to two largely discrete literatures that attempt to explain gender disparities in the hiring and recruiting of female employees. A first set of papers highlights the existence of gender differences in self-assessed abilities on the labor supply side. For example, even after controlling for test scores, female students have been shown to self-assess their level of proficiency as lower than their male classmates (Beyer 1990; Beyer et al. 2003; Correll 2001), to enroll in advanced mathematics courses (Lantz
and Smith 1981), and to choose quantitative careers (Correll 2001). A second and largely discrete literature emphasizes the inequitable treatment of male and female candidates by employers on the labor demand side. Using audit studies, this research carefully measures the extent of discrimination in recruiting (Bertrand and Mullainathan 2004; Riach and Rich 2002; McIntyre, Moberg, and Posner 1980).

Few studies, however, have explored the interaction of gender differences in the actions of job seekers with hiring managers' decisions. The unique dataset used in this paper allows me to observe both gender differences in labor demand behavior, as well as to test if recruiters appear to be responding to such differences in their recruitment decisions.

Overall, while a variety of factors contribute to the underrepresentation of female engineers in tech, my results show evidence of the importance self-promotional behavior in this labor market. Importantly, these findings indicate that neither the labor supply side nor the labor demand side utilizes the self-reporting mechanism in ways that could increase the percentage of women recruited for software engineering positions.
Dropping Anchor: The Effect of a Salary History Ban on Gender-Related Disparities in Compensation
Elliot L. Sherman, Raina Brands and Gillian Ku (London Business School)

Research Question
Could a salary history ban reduce the gender wage gap? Support for this idea continues to build among practitioners and policy-makers alike. In a landmark case, the United States Court of Appeals for the Ninth Circuit ruled: “Women are told they are not worth as much as men. Allowing prior salary to justify a wage differential perpetuates this message, entrenching in salary systems an obvious means of discrimination.” The law resulting from this ruling, AB 168, went into effect on January 1, 2018, at which point it became illegal, in California, to ask a job applicant their current salary. Several other states and cities followed suit, while Google, Amazon, and Starbucks appear to have voluntarily adopted a version of the ban as well. Unfortunately, because salary history bans are introduced unilaterally, it is not possible to construct an adequate control group against which one could credibly measure a treatment effect. Therefore, the purpose of the present research is to design and implement a field experiment which does precisely that.

Theory
During the interview process a candidate’s current salary serves as an anchor, against which hiring managers often insufficiently adjust when making offers (Tversky and Kahneman 1974). As a result, wage gaps can emerge over time between otherwise comparable men and women, conditional on—for example—family-related work interruptions, which women are more likely to experience (Bertrand, Goldin, and Katz 2010). This effect is consistent with the finding that gender-based wage disparities are most common and pronounced at the point of hire (Petersen and Saporta 2004), due to a general lack of oversight and an absence of formal procedures through which applicants could address inequities. Salary history bans, which proscribe managers from asking job applicants to disclose their current salary during the hiring process, could therefore serve as a corrective, insofar as the absence of a salary to anchor on prevents managers from systematically reducing their offers to viable female job candidates. A recent experiment in an online market for freelancers found results that were consistent with this, although gender was unmeasured (Barach and Horton 2017).

However, the same managerial discretion highlighted by Petersen and Saporta (2004) could result in managers simply ignoring the policy, without any clear means for organizational redress. Or, candidates may disclose their current salary during the interview process if they feel it is advantageous to do so, regardless of the policy. Either of these two responses could result in a null effect of treatment. Further, Doleac and Hansen (2016) report the results of a similar attempt to reduce hiring discrimination against felons. This “ban the box” policy, which eliminated a box on hiring forms where felons disclosed their criminal history, actually resulted in greater discrimination against black and Hispanic men. In the absence of disconfirming information, hiring managers appeared to statistically discriminate—generalize from group averages to the individual—which could plausibly occur for women under a salary history ban.

Method and Preliminary Results
The pseudonymous research site for this field experiment is Edco, a mid-sized educational institution located in the United Kingdom. The experiment launched on August 1, 2018, and will continue to run until July 31, 2019. A useful feature of this context is that all staff hiring is centralized through the recruitment team within HR. As a result, the experiment captures the entirety of staff—but not academic faculty—hiring, including through both internal and external channels, that occurs at this research site. This obviates concerns about selection into the experiment.
The treatment was simple. Each time a new role opened, the recruitment team e-mailed the lead author. The lead author then randomized the job to either “green” (control) or “red” (treatment). The treatment precluded hiring managers from asking about the applicant’s current salary. Applicants’ salary was, however, discussed with a member of the HR team before the interview stage, in order to ensure that applicants were reasonably well-calibrated toward the roles under consideration.

Since the experiment began Edco has initiated 181 role searches, of which 132 have closed. At present, we have complete data on 101 of the closed roles; this gap is due to the temporal lag between the successful closing roles and the onboarding of the new hires, as well as the general delays that obtain when gathering survey data at field sites.

Manipulation Check and Assessing Non-Compliance. We created a binary variable that was coded 1 if the hiring manager learned the current salary for at least 1 applicant to a role they were in charge of filling, and 0 otherwise. A t-test indicated that hiring managers in the treatment condition were significantly less likely to know the current salary of at least one applicant to the role for which they were hiring (p = .000). However, while the manipulation was successful in this sense, there were nonetheless examples of non-compliance, due both to candidate disclosure and the fact that the salaries of some internal candidates were already known.

Offer amount. We do not, as yet, observe any significant difference in the offer amount as a function of the treatment. The average offer made is £36,639 and £37,301 in the treatment and control conditions, respectively. At current exchange rates, these equate to about $46,234 versus $47,119.

Raise amount. As our primary dependent variable, we calculated the raise received by each successful candidate by subtracting their current salary from their offer amount. In order to assess the effect of treatment, we regressed the raise amount on an indicator of female, an indicator of treatment, and an interaction between the two. At marginal levels of statistical significance—most likely due to a present lack of statistical power which should be remedied by the time the experiment concludes—this interaction effect is negative. We can therefore report, at this juncture and with respect to this particular setting, that the salary history ban is not having its intended effect, and may actually be accomplishing the opposite.
REFERENCES


Gender Disparities in the Prices that Employers Charge for Their Employees’ Services
Shoshana Schwartz (Wharton Business School)

An influential theory in the study of labor markets argues that the work done by women is devalued by employers, precisely because it is done by women. This theory, known as devaluation theory, argues that the perceived value of work reflects not only the characteristics of the work itself, but also the characteristics of the workers (Cejka & Eagly 1999). Devaluation theory argues that jobs disproportionately held by high-status employees tend to pay more than jobs held by low-status employees, after accounting for the characteristics of the job. Due to status beliefs around gender, men are viewed as more competent and higher-status than women (Broverman et al., 1972; Ridgeway 1997; Ridgeway & England, 2007; Ridgeway, 2011). These beliefs cause people to expect that men will perform better than women (Ridgeway, 2011). Thus, jobs that are predominately filled by women are viewed as less valuable due to the lower status of women. Therefore employers offer lower pay for predominately female jobs than for predominately male jobs.

While prior research has focused on the implications of devaluation theory for pay, I build on this research by arguing that employees’ identities also shape how much employers charge for their work. This underexplored implication of devaluation theory involves potential gender differences in how employers price individuals’ services. In today’s increasingly knowledge-based economy, employers often have to determine how much to charge customers and clients for work performed by their employees. The price that the employer charges clients and customers for employees’ services reflects characteristics of the work such as difficulty and complexity, as well as characteristics of the employees performing the work such as their experience and skill. If employers devalue women’s work as posited by devaluation theory, then employers would charge less for work performed by female employees than for equivalent work performed by equally-skilled male employees.

As prices reflect not only economic forces of supply and demand (Mankiw, 2014) but also sociological factors that influence perceptions of quality and willingness to pay (Beckert, 2011), employers may set different prices for the same work performed by employees possessing different levels of social status. As discussed earlier, gendered cultural beliefs exist such that men possess higher social status than women and are expected to have better performance (Ridgeway, 2011). Therefore, if women’s work is devalued, then employers would charge less for work performed by women than for equivalent work performed by men.

Thus, I hypothesize the following:

**Hypothesis 1:** During employees’ tenures in a job, the price that employers charge customers and clients for work performed by female employees decreases relative to price that employers charge customers and clients for equivalent work performed by male employees.

**Model**

I study whether employers devalue female employees when setting the price that they charge clients and customers for their employees’ work. My study context is the mutual fund industry. In my context, mutual fund managers are employees of the mutual fund sponsor company (the employer). Mutual fund managers are assigned to manage mutual funds. Mutual funds charge investors (who are the clients/customers) a management fee. The management fee represents the price that the employer charges for the mutual fund manager’s services. The management fees are generally determined by mutual fund
employers (upper management), subject to board approval (i.e., not by the mutual fund managers themselves). This leads to the model summarized in Table 1 below.

<table>
<thead>
<tr>
<th>General Case</th>
<th>In Mutual Fund Industry Context</th>
</tr>
</thead>
<tbody>
<tr>
<td>Employer</td>
<td>mutual fund sponsor company</td>
</tr>
<tr>
<td>Employee</td>
<td>mutual fund manager</td>
</tr>
<tr>
<td>customer/client</td>
<td>investors</td>
</tr>
<tr>
<td>price of employee's services</td>
<td>management fee</td>
</tr>
<tr>
<td>sets price of employee's services</td>
<td>mutual fund upper management (subject to approval from board of directors)</td>
</tr>
</tbody>
</table>

**Method**

This is an econometric analysis. I regress a given mutual fund’s management fees on the mutual fund manager’s gender and manager-level, fund-level, and firm-level controls, including an unbiased and complete measure of performance. Fund fixed effects also allow me to ensure that I’m comparing men and women who are truly performing the same job, i.e. managing the same fund. Additionally, I conducted interviews with mutual fund managers to inform the model and the interpretation of my quantitative results.

Data are taken from MorningStar and CRSP. Analysis is based on matched manager-level, fund-level, and firm-level data for over 13,000 mutual fund managers across over 8,000 mutual funds from 2000-2014.

**Figure 1: Overview of Data**

- **CRSP Mutual Fund Data**
  - Management fees

- **MorningStar: Share-class-level**
  - Assets
  - Returns

- **MorningStar: Firm-level**
  - Firm assets
  - Number of funds offered

- **MorningStar: Fund-level**
  - Fund Type
  - Fund Objective
  - Fund Management Company

- **Market Data**
  - Federal Reserve T-Bill Data
  - CRSP market indices

- **MorningStar: Manager-level**
  - Funds Managed
  - Start / end dates for each fund managed
  - Gender
  - Education
  - Birthday

merge

aggregate

match
**Abbreviated Findings**

My research finds strong evidence that employers have gender bias when determining how to charge customers and clients for work performed by their male and female employees. During employees’ time in a mutual fund manager position, employers charge increasingly less for female-managed funds than for male-managed funds, as shown by the negative coefficient on “female * time in position” in table 2 below. This difference is not explained by employees’ qualifications nor by gender differences in performance. This is evidence in support of hypothesis 1, that employers devalue women when determining the price to charge customers and clients for their employees’ work.

### Table 2: Changes in Management Fees During Individuals’ Tenures in Specific Job

<table>
<thead>
<tr>
<th>VARIABLES</th>
<th>(1)</th>
<th>(2)</th>
<th>(3)</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Management Fee</td>
<td>Management Fee</td>
<td>Management Fee</td>
</tr>
<tr>
<td>Female</td>
<td>-0.0152***</td>
<td>0.00184</td>
<td>0.00417**</td>
</tr>
<tr>
<td></td>
<td>(0.00517)</td>
<td>(0.00170)</td>
<td>(0.00184)</td>
</tr>
<tr>
<td>Time in Position</td>
<td>0.000228***</td>
<td>0.000226***</td>
<td></td>
</tr>
<tr>
<td></td>
<td>(2.77e-05)</td>
<td>(2.95e-05)</td>
<td></td>
</tr>
<tr>
<td>Female * Time in Position</td>
<td>-0.000243***</td>
<td>-0.000275***</td>
<td></td>
</tr>
<tr>
<td></td>
<td>(5.59e-05)</td>
<td>(5.81e-05)</td>
<td></td>
</tr>
<tr>
<td>Time Controls</td>
<td>x</td>
<td>x</td>
<td>x</td>
</tr>
<tr>
<td>Fund Manager Controls</td>
<td>x</td>
<td>x</td>
<td></td>
</tr>
<tr>
<td>Fund Controls</td>
<td>x</td>
<td>x</td>
<td></td>
</tr>
<tr>
<td>Management Company Controls</td>
<td>x</td>
<td>x</td>
<td></td>
</tr>
<tr>
<td>Fund Performance</td>
<td></td>
<td>x</td>
<td></td>
</tr>
<tr>
<td>Fund Fixed Effects</td>
<td>x</td>
<td>x</td>
<td></td>
</tr>
<tr>
<td>Constant</td>
<td>0.635***</td>
<td>-2.293</td>
<td>-1.965</td>
</tr>
<tr>
<td></td>
<td>(0.00217)</td>
<td>(3.385)</td>
<td>(2.616)</td>
</tr>
<tr>
<td>Observations</td>
<td>653,899</td>
<td>355,874</td>
<td>289,317</td>
</tr>
<tr>
<td>Number of mgrcode_fundidN</td>
<td>41,268</td>
<td>26,661</td>
<td>21,038</td>
</tr>
</tbody>
</table>

Standard errors in parentheses

*** p<0.01, ** p<0.05, * p<0.1

Notes:
- Management Fee (DV) lagged one quarter.
- Fund Manager (Employee) controls include: non-MBA advanced degree (indic), MBA degree (indic), CFA (indic), age, objective, SRI indic, FoF indic, turnover, alpha RAR RS (lag), asset flows (lag).
- Management Company (Firm) controls include: size in total assets and size in number of funds
- Asset flows are in level. Results hold when asset flows are in winsorized percent.
- Time year-quarter.
- Unit-level is manager-fund-time (e.g., manager, at fund, during time).
Gender Segregation as a Dynamic Process: The Cyclical Effect of Gender Composition On Occupational Entry in Medicine  

Allison Elias (Wharton Business School) and Jirs Meuris (University of Wisconsin)

Occupational gender segregation has been argued to originate from a combination of supply- and demand-side factors that hinder recruitment and retention (Fernandez-Mateo and Kaplan, 2018). Although there is evidence that applicants from the non-dominant gender in the occupation are frequently disadvantaged throughout the selection process, they also often don’t apply for entry in the first place (Fernandez and Frierich, 2010). Barbulescu and Bidwell (2013) argue that the decision to forego application despite qualification is driven by the non-dominant gender’s perceived lack of identification with the occupation and anticipation of a low likelihood of acceptance if they would apply. One factor that is assumed to influence these subjective appraisals is the gender composition of the occupation. Specifically, as gender disparities within an occupation widen, the non-dominant gender should be less likely to feel that they belong within the occupation and more likely to anticipate a low likelihood of acceptance if they do apply, and thus, one would assume that supply and entry to the occupation subsequently decline. However, limited theoretical and empirical attention has been devoted to the assumed relationship between gender composition and gender-based differences in occupational entry, partly attributable to the difficulty of disentangling the direction of causality between them (Barbulescu and Bidwell, 2013).

This paper aims to contribute to our understanding of how occupations become (de)segregated by developing a dynamic model of the relationship between gender composition and occupational entry within the context of medical specialties. In contrast to the linear perspective taken by most prior studies in this literature, we adopt an episodic approach that considers gender (de)segregation as a cyclical process where it unravels over time as the characteristics of new entrants shape the composition of subsequent applicant pools. We propose that the supply of the non-dominant gender into a specialty constitutes two decisions: (a) application for entry and (b) how much they invest into gaining entry given limited time and resources. Our model argues that the gender composition of residents within the specialty, the gender composition of recent entrants, and the competitiveness of entry to the specialty each independently affect these decisions by altering the perceived identification with the specialty and/or anticipated likelihood of acceptance. We therefore hypothesized that changes in the gender composition of residents in the specialty, gender composition of new entrants, and competitiveness will influence the gender gap in application rates and average number of applications submitted per person in the following year. As gender differences in application to the specialty and number of applications submitted decrease, we further expected that the gender gap in entry declines due to the increasing supply of the non-dominant gender, which provides novel input that determines the gender composition of the following year’s applicant pool. In short, as gender differences in composition approach parity, gender differences in supply get smaller, and thus, the gender gap in entry will decline, which influences these dynamics the following year.

To test our model, we use a multi-source archival dataset covering thirteen medical specialties from 2005 to 2017 (see Table 1 for variable descriptions). Since our theory proposes a cyclical relationship among the variables, we constructed a structural equation model with Bayesian estimation, an under-utilized, yet highly relevant methodological approach to studying the mechanisms underlying sociological and organizational phenomena. The advantage of this approach is that we can model the hypothesized effects simultaneously rather than across a series of separate regression equations. Bayesian estimation was chosen given the evidence for its superior performance to maximum likelihood in limited sample sizes (Gelman et al., 2013; Yuan and MacKinnon, 2009). All variables were group-mean centered because we were only interested in the within-specialty changes among the variables over time.
Our results generally support the dynamic model proposed in this paper (see Figure 1). We find that the gender composition of residents in the specialty has an indirect effect on gender differences in entry into the specialty by shifting the gender gap in application rates and the average number of applications each person submits. The ratio of men and women that enter residencies within the specialty, in turn, indirectly affects the gender gap in application rates and the average number of applications each person submits in the following year by changing the gender composition, but also has an independent direct effect on gender differences in application rates. Furthermore, as the competitiveness of entry into the specialty increases, we find that women are not less likely to apply than men but those who do submit a lower number of applications on average. Collectively, our findings demonstrate a cyclical relationship between the gender representation within an occupation and gender differences in entry through alterations in the labor supply within the context of medicine, and thus, provide a foundation for understanding the dynamic mechanisms underlying gender (de)segregation over time.

Figure 1. Analytic model

Notes: Blue arrows represent a significant positive effect; red arrows represent a significant negative effect. All paths where the credible interval includes 0 are omitted from the figure. All paths control for number of positions available at year \( t \).

Table 1. Description of Variables

<table>
<thead>
<tr>
<th>Variable</th>
<th>Description</th>
</tr>
</thead>
<tbody>
<tr>
<td>Gender composition of specialty</td>
<td>The percentage of residents within the specialty that are female.</td>
</tr>
<tr>
<td>Competitiveness of specialty</td>
<td>The fill rate of the specialty, defined as the number of US medical school graduates (USMG) who enter the specialty relative to total entrants (USMG and graduates of foreign medical schools). Widely used measure of competitiveness of the specialty in the medical literature.</td>
</tr>
<tr>
<td>Gender gap in applications</td>
<td>The application rate among men divided by the application rate among women. Larger values signify that more men applied to the specialty than women.</td>
</tr>
<tr>
<td>---------------------------</td>
<td>--------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------</td>
</tr>
<tr>
<td>Gender gap in average number of applications</td>
<td>The average number of applications per person among men divided by the average number of applications per person among women. Larger values signify that each male applicant submitted more applications on average to the specialty than each female applicant.</td>
</tr>
<tr>
<td>Gender differences in entry</td>
<td>The entry rate among men divided by the entry rate among women. Larger values signify that more men entered the specialty for time $t$ relative to women.</td>
</tr>
</tbody>
</table>
References


Gender and the Interpretation of Endorsement Ties: Evidence from Entrepreneurial Financing
Kaisa Snellman and Isabelle Solal (INSEAD)

When quality is difficult and costly to observe, evaluators tend to rely on external cues to make inferences about an individual or firm. In the absence of other information, employers use education to distinguish low ability workers from high ability workers (Spence 1973, 1974), consumers may rely on the length of the warranty to guide their selection (Akerlof 1970), and investors may infer that firms named after their founder are going to be more profitable (Belenzon, Chatterji, and Daley 2017). Third-party endorsements can help reduce uncertainty and thereby resolve market inefficiencies. Partnering with a prominent organization may help a nascent start-up gain legitimacy (Baum and Oliver 1991; Podolny 1994), a referral may open doors for a job applicant (Fernandez, Castilla, and Moore 2000), and having a recommendation from an alumnus may help aspiring students gain admission (Castilla and Rissing 2019). An endorsement from a third party reduces uncertainty by signaling to the market that the endorser possesses some private information about the party being endorsed. As a result, observers can rely on the endorser’s own evaluation of quality. The extent to which the endorsement is effective, however, will depend on how it is interpreted.

Far from being unequivocal, most signals are ambiguous and are subject to interpretation by observers (Plummer, Allison, and Connelly 2016). In this paper, we theorize that characteristics of the parties in an endorsement relationship can change the interpretation of the signal and bias the estimate of quality. This is notably the case for demographic characteristics, such as gender or race, that have acquired independent status value and are associated with certain expectations of competence (Ridgeway 1991). We argue that observers consider the status characteristics of the endorser and endorsee jointly. The characteristics of the endorser may make the status characteristic of the endorsee more or less salient, thus either amplifying or reducing the endorsement’s effect. In a context where there is a perceived lack of fit between stereotypes associated with women and those associated with success in a profession, female-female endorsement ties will increase the salience of gender and affect attributions of motivation for the endorsement, in a manner that reduces the value of the signal for the endorsed female.

We test our argument in the market for entrepreneurial capital. Affiliation with an investor can reduce uncertainty regarding the quality of early-stage ventures (Sorenson and Stuart 2008; Stuart, Hoang, and Hybels 1999). Moreover, the way audiences make sense of investor endorsements is influenced by other available information, such as investor prominence, market conditions, or the timing of the investment (Gulati and Higgins 2003; Lee, Pollock, and Jin 2011; Stuart et al. 1999). We argue that investor and entrepreneur gender serve as cues to the market that frame the interpretation of endorsement signals. In particular, we suggest that female entrepreneurs will be evaluated more favorably if they are affiliated with a male investor than if they have an affiliation with a female investor. In a male-typed setting such as entrepreneurship, where female entrepreneurs are underrepresented and do not fit the ideal type, female-female pairing are highly visible, increasing the salience of gender and activating competence stereotypes.

We first tested our predictions using archival data on early-stage venture capital investment in female-led ventures in the United States. Employing an event-history analysis, we find that those firms funded by only female investors take longer to raise additional capital than female-led firms whose first-round investors include male investors. However, drawing causal inference from archival data is challenging given the possible confounding effects of selection, sorting, and treatment. To address these concerns, we first compare our results with those from a control sample of firms with all-male founding teams, and find no equivalent effect of investor gender for these male-founded firms. Then, to strengthen
our causal interpretation and to test our proposed underlying mechanism, we conducted an experimental study, where we measured perceptions of entrepreneurs and their ventures, manipulating the gender of both the entrepreneur and the investor. We find that the gender of an early backer influences perceptions of quality for pitches by female, but not male, entrepreneurs, and that this is due to audiences discounting the female entrepreneur’s competence when she is championed by a woman.

Our research contributes to the signaling literature by examining how additional cues surrounding the signal affect its interpretation and impact. Our work further speaks to the literature on gender and social capital, suggesting how differential returns to homophily for men and women may be due not only to disparities in resource distribution, but also shaped by the interpretations made by the audience. Finally, we contribute to research on female entrepreneurship by highlighting a mechanism through which gender-biased evaluations structure the market for entrepreneurial capital.
Re-Patterning the Social Networks of Nashville Songwriters: Structural Determinants of Careers in Informal Workplaces
Rachel Skaggs (Ohio State University)

What is the effect of the macro political economic or industry conditions on how workers in informal occupational communities collaborate and how, in turn, does a worker’s structural location in a social network of collaborators affect his or her likelihood of career success?

I answer this question through a combination of interviews, whole network analysis, network visualization, and a multivariate statistical analysis of individual songwriters’ network centrality on their likelihood of success in writing hit songs during different periods of time during an era of increasing precarity and monumental change in the music industry. I use the case-in-point of Nashville songwriters, artists who work in a geographically concentrated labor market to formulate questions that guides my research about collaboration as a strategy to deal with uncertainty in career pathways situated within a post-bureaucratic employment relation. According to Billboard Magazine, Nashville, Tennessee is home to 27,000 music industry workers, which at 7.8 music professionals per 1,000 residents gives it the highest concentration of music industry workers in the United States (Peoples 2013). The high density of music professionals makes Nashville a good case for examining the field of music production. Songwriting is a collaborative business in Nashville, and most hit country songs are co-written. Songwriters (de Laat 2015) and the Nashville music community more broadly (Cornfield 2015) are known to collectivize responses to the uncertainty of the music industry through collaboration with peers, structured mentorship, and new forms of labor and craft union organizing.

Nashville songwriters often talk about “writing up,” showing awareness that they need to collaborate with high-status, well-connected writers to raise their own status and thus, their chance of success in the music industry. Songwriters may have a “staff songwriting” job as an employee of a publishing company, but for the most part, songwriters are free agents. In an interview with the director of a local trade organization, I was told that whereas there were about 1000 staff songwriting positions in Nashville in the 1990s that now there are closer to 300. As the decline in staff songwriting jobs suggests, the political economy of the music industry has undergone a great deal of change since the turn of the millennium. Revenues have declined precipitously in response to the new digital music economy.

In this study, I examine changes in songwriter social network cohesion and its impact on songwriter careers from 2000-2015. This chapter comes from my dissertation and is part of a larger, multi-method project using my novel network-based sampling frame approach to examine interviews, social network data, and macro industry-level data within a given community. In my interviews with songwriters, there emerged a clear series of events that caused their co-writing strategy to shift after the turn of the last century. Because of decreasing music industry revenues, the so-called 360˚ deal became the norm for recording artist contracts such that recording artists are contractually obligated to write a portion of their own music. This new kind of contract further closed the window of opportunity for songwriters to get “outside cuts” on albums without co-writing with the album’s recording artist. In response, songwriters increasingly choose to co-write with recording artists to enhance their chances of success.

This presentation will highlight findings from my multi-method study of songwriter social networks: From logistic regression analyses it is clear that the composition of co-writing groups has changed in terms of the number and primary occupation of collaborators. Social network analysis on the whole network of successful songwriters during the period of study, results show that the macro-network
structure becomes more cohesive in each subsequent year. Qualitative interviews illustrate how individual songwriters strategically engage in collaboration to enhance their chances of having a song recorded and released on a commercial country album.

The line of scholarship I have laid out above provides a perspective that accounts for networked behavior around the production of artistic works, but the perspective may be generalized to a variety of free-agentic occupational contexts. When opportunity is concentrated in social space, people seeking opportunity will try to collaborate with highly connected people in the network. If we further incorporate Becker’s (1982) concept of patterned cooperation between individuals holding different occupational roles in art worlds, it is apparent that collaboration between individuals holding different occupational roles could streamline the social pathways that connect individuals to opportunity.

References:
Generalists, Specialists and Changes to the Knowledge Landscape

Shinjinee Chattopadhyay (University of Illinois)

Organizations evolve with the science of the field (Helfat & Peteraf, 2003). Firms routinely embark on new search processes and source new knowledge to remain relevant and innovative (Cyert and March, 1963; Fleming, 2001; Katila and Ahuja, 2002). As organizations change, workers must adjust, but workers’ responses to change are not uniform. Recent literature has intimated that knowledge workers may have varied responses to changing contexts. Specialized scientists with focused knowledge are more readily able to adjust to rapid expansion in the knowledge frontier than scientists holding more diversified knowledge (Teodoridis, et al., 2018). Indeed, specialized individuals with narrow, deep expertise have unique strengths and weaknesses relative to generalized individuals with wide-spanning knowledge. Given these differences, it is important to understand contingencies under which they perform differently. Further investigation into the response of diversified vs. specialized inventors allows us to gain insights into how organizations may better leverage their human resources as they go through technological disruptions.

Going through an acquisition is one such technological shift that brings about many organizational changes and is an appropriate context to study. Acquisitions are an important means by which firms access external knowledge to contend with evolving technologies (Puranam, Singh, & Zollo, 2003), particularly in scientific industries such as pharmaceuticals. Inventors endure productivity losses following acquisitions on account of disruption to their knowledge networks, and misalignment of routines and incentives of the acquiring and target firms (Paruchari, et al. 2006; Kapoor & Lim, 2007). Since access to human talent is one of the driving reasons for acquisitions it is crucial to understand reasons why some knowledge workers remain productive after acquisitions and why some do not.

Acquisitions will influence inventors’ ability to continue to invent by altering the value proposition of existing knowledge within the firm. On one hand new boundary-spanning knowledge obtained through acquisitions provides inventors opportunities to engage in novel recombination with existing knowledge, leading to potentially-pathbreaking innovation (Ahuja & Katila, 2001; Rosenkopf & Nerkar, 2001; Makri, Hitt, & Lane, 2011). On the other hand, the influx of new knowledge may result in a pivot in R&D investments and the innovation trajectory of the firm, rendering incumbent knowledge obsolete (Tushman & Anderson, 1986). Diversified inventors will presumably face a different set of innovative opportunities and constraints compared to specialists.

This paper theorizes that acquisitions bring about two main changes that generalists are able to navigate better than specialists: access to new knowledge (Ahuja & Katila, 2001) and the obsolescence of incumbent knowledge (Vermuelen & Barkema, 2001). First, generalists are able to absorb and integrate boundary-spanning knowledge sought through acquisitions on account of the higher breadth of knowledge yielding higher absorptive capacity across different areas (Cohen & Levinthal, 1991). Since new inventions result from the integration and combination of existing and new knowledge (Fleming, 2001) wider-spanning knowledge will thus have the potential to create a larger set of recombinations and therefore, inventions. Second, generalists are better able to reorient if knowledge is rendered redundant. After the acquisition of Genentech in 2009, Roche the acquirer, eliminated incumbent research lines such as RNA interference and pivoted to discovering pathways for targeted therapeutics7 thereby potentially altering the

---

7 https://xconomy.com/san-francisco/2012/05/29/genentech-roche-find-new-balance-three-years-post-merger/
Last accessed on May 23, 2019
research agendas of thousands of inventors. In such cases, generalists’ wide-spanning knowledge across different areas will endow them with a higher probability to remain productive even if much of the incumbent knowledge is rendered redundant. Specialists, having most of their knowledge in fewer baskets will face a higher likelihood of becoming obsolete. Moreover, generalists with their wide-spanning knowledge are able to retool and upgrade their skills faster than specialists.

Using a sample of inventors from 159 technology acquisitions in the pharmaceutical industry this study uses a coarsened exact matching (CEM) technique to examine the productivity outcomes of 10,988 inventors belonging to the acquiring and target firms. This paper finds that while only 36 percent of previously-patenting inventors continue to patent after acquisitions, *ceteris paribus* inventors holding generalized knowledge are significantly more likely than specialized inventors to do so. We further find that while on average inventors experience a productivity drop following acquisitions, generalist inventors suffer a lower drop in patenting quality and quantity than specialist inventors. Moreover, technological similarity with the acquired firm positively moderates patenting quantity of specialists, while technologically dissimilarity positively moderates that of generalists.

This paper makes contributions to the literature studying rewards to individual-level specialization (Leung, 2014; Zuckerman et al., 2003; Leahey, 2007; Ferguson & Hasan, 2013; Phillips & Merluzzi, 2016) by raising the intriguing possibility that generalists’ strengths while not always readily apparent can nevertheless be valuable to firms, especially after disruptive changes. Moreover, the insight that generalists are better suited for reorienting has implications that are consequential for all organizations and managers.
The Employment Consequences of Robots: Firm-Level Evidence
Jay Dixon (Statistics Canada), Bryan Hong (NYU Stern) and Lynn Wu (Wharton Business School)

Robotics and artificial intelligence (AI) have shown great potential to be the next engine of innovation and productivity growth in the global economy (CEA 2016). As their capabilities grow, robots are expected to replace a wide range of labor-intensive as well as cognitively demanding tasks, potentially leaving human labor with substantially fewer activities that can add value (Brynjolfsson and McAfee 2014, Ford 2015). If true, this would lead to severe negative consequences for employment in the labor force as technology automates a large proportion of labor. However, robots and AI have also been argued to be similar to past generations of general-purpose technologies (GPT) that ultimately increased labor demand. In this competing view, even as labor is displaced as the result of technology adoption, new jobs are also created and the associated gains in employment that complement the new technology will compensate for the number of jobs lost.

Thus far, actual empirical evidence connecting robots and employment has been limited, in part due to the lack of microdata at the firm level measuring robot adoption. Instead, empirical studies examining the effect of robots on labor have relied upon much coarser data at the level of industry or geographic region (Graetz and Michaels 2015, Mann and Püttmann 2017). These studies largely predict a drastic decline in overall employment and labor share with robot investments (Acemoglu and Restrepo 2017, Dinlersoz and Wolf 2018, Graetz and Michaels 2015, Mann and Püttmann 2017). However, analysis at the industry and country level is insufficient to show the mechanisms through which firms are using robotics to substitute labor, and to what extent AI and robots can complement labor to generate new labor demand (Autor and Salomons 2018). Ultimately, firm-level analysis is necessary to examine the extent to which firms benefit from robotics, and how they may substitute or complement labor (Acemoglu and Restrepo 2017, Brynjolfsson et al. 2018, Brynjolfsson et al. 2018).

In this study, we provide the first firm-level evidence of the effect of robots on labor using comprehensive data containing measures of robot investments, employment, and firm practices for firms in the Canadian economy. Using panel data from 2000 to 2015, we find that, contrary to the popular press and earlier studies at the industry and geographic region level, robot adoption does not predict employment declines, but is instead associated with increases in labor (see Table 1). Our findings are consistent with the effects of prior GPTs that have been shown to increase both employment and productivity. As additional evidence that robots are not adopted primarily as a cost-cutting effort to reduce labor, we also find that robot adoption is not associated with an increase in the strategic importance of reducing labor costs for firms, but is instead associated with an increase in the strategic importance of improving product and service quality (see Table 2).

With respect to labor composition effects, we find that robot adoption predicts the displacement of managers even though overall employment increases, with robot investments predicting both decreases in managerial hiring and increases in managerial turnover (see Table 1). By contrast, we observe an increase in both hiring and turnover of non-managerial employees. The displacement of managers over non-managerial employees differs from previous studies examining the effect of prior information technologies that found that IT generally displaced low- and middle-skilled workers (Autor et al. 2006, Autor et al. 2003, Murnane et al. 1999). Here, we find evidence that robots displace labor with higher cognitive requirements in managerial positions. These results suggest a compositional change in labor in response to changes in the nature of work as the result of robot investment. Consistent with this view, we find that firms invest more in training employees to work with technologies (see Table 4). Similarly,
we also find that robot investments are associated with a reduction of decision authority for managers with respect to employee training and choice of production technology (see Table 3). For employee training, decision authority is decentralized downwards to non-managerial employees while the choice of production technology is centralized upwards to business owners and corporate headquarters. These results show that not only has employment changed due to robots, but the change is related to complementary work practices that are critical to the understanding of how robots affect labor. While our analysis provides only initial firm-level evidence, our comprehensive set of outcomes—employment, labor composition, strategic priorities, allocation of decision rights, and training—suggest that robots have a substantive effect on both employment and work practices that differs from prior technologies. Overall, our results show the importance of examining the effect of robot investment at the firm level and contribute to the important debate about the consequences of robot investments on labor.
Figure 1. Aggregate robot stock in Canada 1996-2017

Figure 2. Robot investment attributable by economic sector, 2000-2017
Table 1. Employment regressions

<table>
<thead>
<tr>
<th></th>
<th>(1)</th>
<th>(2)</th>
<th>(3)</th>
<th>(4)</th>
<th>(5)</th>
<th>(6)</th>
<th>(7)</th>
<th>(8)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Dataset:</td>
<td>NALMF</td>
<td>WES</td>
<td>WES</td>
<td>WES</td>
<td>WES</td>
<td>WES</td>
<td>WES</td>
<td>WES</td>
</tr>
<tr>
<td>ln(Total employees)</td>
<td>0.191***</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>ln(Total managers)</td>
<td>0.084***</td>
<td>0.243***</td>
<td>0.005</td>
<td>-0.046</td>
<td>-0.005</td>
<td>-0.049</td>
<td>-0.036</td>
<td></td>
</tr>
<tr>
<td>ln(Total non-mgr. employees)</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Mgr. Hiring Rate</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Nonmgr. Hiring Rate</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Mgr. Turnover</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Nonmgr. Turnover</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Outside recruitment</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>ln(Total assets)</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>ln(Total revenues)</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Multi-unit enterprise</td>
<td>0.139***</td>
<td>0.032</td>
<td>0.046</td>
<td>0.034</td>
<td>0.012</td>
<td>-0.036</td>
<td>-0.034</td>
<td>-0.024</td>
</tr>
<tr>
<td>Unionized</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>ln(Robot capital stock)</td>
<td>0.007***</td>
<td>-0.080***</td>
<td>0.005**</td>
<td>-0.007***</td>
<td>0.013***</td>
<td>0.044***</td>
<td>0.012***</td>
<td>0.024***</td>
</tr>
<tr>
<td>Year fixed effects</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Organization fixed effects</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Observations</td>
<td>929,162</td>
<td>17,449</td>
<td>17,449</td>
<td>17,449</td>
<td>17,449</td>
<td>17,449</td>
<td>17,449</td>
<td>16,522</td>
</tr>
<tr>
<td>Adj R-squared</td>
<td>0.92</td>
<td>0.69</td>
<td>0.88</td>
<td>0.19</td>
<td>0.58</td>
<td>0.04</td>
<td>0.30</td>
<td>0.39</td>
</tr>
</tbody>
</table>

Standard errors in parentheses, clustered by industry. All regressions using WES data use sampling weights. *** p<0.01, ** p<0.05, * p<0.1

Table 2. Strategic priority regressions

<table>
<thead>
<tr>
<th></th>
<th>(1)</th>
<th>(2)</th>
<th>(3)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Dataset:</td>
<td>FE</td>
<td>FE</td>
<td>FE</td>
</tr>
<tr>
<td>Dependent variable (strategic importance):</td>
<td>Reducing labor costs</td>
<td>Reducing other operating costs</td>
<td>Improving product/service quality</td>
</tr>
<tr>
<td>ln(Total revenues)</td>
<td>-0.111</td>
<td>0.049</td>
<td>0.105</td>
</tr>
<tr>
<td>Multi-unit enterprise</td>
<td>-0.199</td>
<td>0.178</td>
<td>-0.201</td>
</tr>
<tr>
<td>Unionized</td>
<td>-0.144</td>
<td>-0.527***</td>
<td>-0.335*</td>
</tr>
<tr>
<td>ln(Robot capital stock)</td>
<td>0.027</td>
<td>-0.117***</td>
<td>0.107***</td>
</tr>
<tr>
<td>Year fixed effects</td>
<td>Y</td>
<td>Y</td>
<td>Y</td>
</tr>
<tr>
<td>Organization fixed effects</td>
<td>Y</td>
<td>Y</td>
<td>Y</td>
</tr>
<tr>
<td>Observations</td>
<td>8,906</td>
<td>8,906</td>
<td>8,906</td>
</tr>
<tr>
<td>Adj R-squared</td>
<td>0.32</td>
<td>0.34</td>
<td>0.38</td>
</tr>
</tbody>
</table>

Standard errors in parentheses, clustered by industry. All regressions use sampling weights. *** p<0.01, ** p<0.05, * p<0.1
Table 3. Task allocation regressions

<table>
<thead>
<tr>
<th></th>
<th>(1)</th>
<th>(2)</th>
<th>(3)</th>
<th>(4)</th>
<th>(5)</th>
<th>(6)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Dependent variable:</td>
<td>FE</td>
<td>FE</td>
<td>FE</td>
<td>FE</td>
<td>FE</td>
<td>FE</td>
</tr>
<tr>
<td>Non-managerial employees</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Managers</td>
<td>-0.001</td>
<td>0.000</td>
<td>0.019</td>
<td>0.002</td>
<td>0.061</td>
<td>-0.049</td>
</tr>
<tr>
<td>Business owners or Corp HQ</td>
<td>(0.018)</td>
<td>(0.084)</td>
<td>(0.084)</td>
<td>(0.007)</td>
<td>(0.067)</td>
<td>(0.070)</td>
</tr>
<tr>
<td>Multi-unit enterprise</td>
<td>0.010</td>
<td>-0.022</td>
<td>0.107</td>
<td>-0.008</td>
<td>0.039</td>
<td>0.069</td>
</tr>
<tr>
<td></td>
<td>(0.013)</td>
<td>(0.077)</td>
<td>(0.102)</td>
<td>(0.012)</td>
<td>(0.065)</td>
<td>(0.095)</td>
</tr>
<tr>
<td>Unionized</td>
<td>-0.041</td>
<td>-0.071</td>
<td>-0.141</td>
<td>-0.001</td>
<td>0.232</td>
<td>-0.527***</td>
</tr>
<tr>
<td></td>
<td>(0.139)</td>
<td>(0.212)</td>
<td>(0.174)</td>
<td>(0.004)</td>
<td>(0.190)</td>
<td>(0.182)</td>
</tr>
<tr>
<td>ln(Robot capital stock)</td>
<td>0.074***</td>
<td>-0.077***</td>
<td>0.004</td>
<td>-0.000</td>
<td>-0.069***</td>
<td>0.075***</td>
</tr>
<tr>
<td></td>
<td>(0.011)</td>
<td>(0.011)</td>
<td>(0.003)</td>
<td>(0.000)</td>
<td>(0.015)</td>
<td>(0.013)</td>
</tr>
<tr>
<td>Year fixed effects</td>
<td>Y</td>
<td>Y</td>
<td>Y</td>
<td>Y</td>
<td>Y</td>
<td>Y</td>
</tr>
<tr>
<td>Organization fixed effects</td>
<td>Y</td>
<td>Y</td>
<td>Y</td>
<td>Y</td>
<td>Y</td>
<td>Y</td>
</tr>
<tr>
<td>Observations</td>
<td>6,173</td>
<td>6,173</td>
<td>6,173</td>
<td>6,173</td>
<td>6,173</td>
<td>6,173</td>
</tr>
<tr>
<td>Adj R-squared</td>
<td>0.29</td>
<td>0.33</td>
<td>0.39</td>
<td>0.30</td>
<td>0.31</td>
<td>0.33</td>
</tr>
</tbody>
</table>

Standard errors in parentheses, clustered by industry. All regressions use sampling weights. *** p<0.01, ** p<0.05, * p<0.1

Table 4. Training regressions

<table>
<thead>
<tr>
<th></th>
<th>(1)</th>
<th>(2)</th>
<th>(3)</th>
<th>(4)</th>
<th>(5)</th>
<th>(6)</th>
<th>(7)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Dependent variable</td>
<td>FE</td>
<td>FE</td>
<td>FE</td>
<td>FE</td>
<td>FE</td>
<td>FE</td>
<td>FE</td>
</tr>
<tr>
<td>(type of training):</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Computer hardware</td>
<td>0.042</td>
<td>0.065</td>
<td>0.027</td>
<td>0.052</td>
<td>0.032</td>
<td>0.059</td>
<td>0.018</td>
</tr>
<tr>
<td></td>
<td>(0.032)</td>
<td>(0.044)</td>
<td>(0.031)</td>
<td>(0.036)</td>
<td>(0.029)</td>
<td>(0.050)</td>
<td>(0.037)</td>
</tr>
<tr>
<td>Professional</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Other office and non-office equipment</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Team-building, leadership, communication</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Group decision-making or problem-solving</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Orientation</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Apprentice-ship</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>ln(Total revenues)</td>
<td>0.020***</td>
<td>0.034***</td>
<td>-0.034***</td>
<td>0.003</td>
<td>-0.000</td>
<td>-0.002</td>
<td>0.000</td>
</tr>
<tr>
<td></td>
<td>(0.003)</td>
<td>(0.005)</td>
<td>(0.005)</td>
<td>(0.004)</td>
<td>(0.002)</td>
<td>(0.003)</td>
<td>(0.003)</td>
</tr>
<tr>
<td>Multi-unit enterprise</td>
<td>-0.003</td>
<td>-0.076</td>
<td>0.031</td>
<td>0.164*</td>
<td>0.065</td>
<td>-0.069</td>
<td>0.036</td>
</tr>
<tr>
<td></td>
<td>(0.034)</td>
<td>(0.054)</td>
<td>(0.033)</td>
<td>(0.094)</td>
<td>(0.044)</td>
<td>(0.075)</td>
<td>(0.065)</td>
</tr>
<tr>
<td>Unionized</td>
<td>0.014</td>
<td>-0.014</td>
<td>-0.002</td>
<td>-0.150*</td>
<td>0.028</td>
<td>-0.060</td>
<td>-0.014</td>
</tr>
<tr>
<td></td>
<td>(0.055)</td>
<td>(0.063)</td>
<td>(0.066)</td>
<td>(0.077)</td>
<td>(0.034)</td>
<td>(0.058)</td>
<td>(0.039)</td>
</tr>
<tr>
<td>ln(Robot capital stock)</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Year fixed effects</td>
<td>Y</td>
<td>Y</td>
<td>Y</td>
<td>Y</td>
<td>Y</td>
<td>Y</td>
<td>Y</td>
</tr>
<tr>
<td>Organization fixed effects</td>
<td>Y</td>
<td>Y</td>
<td>Y</td>
<td>Y</td>
<td>Y</td>
<td>Y</td>
<td>Y</td>
</tr>
<tr>
<td>Observations</td>
<td>17,449</td>
<td>17,449</td>
<td>17,449</td>
<td>17,449</td>
<td>17,449</td>
<td>17,449</td>
<td>17,449</td>
</tr>
<tr>
<td>Adj R-squared</td>
<td>0.38</td>
<td>0.47</td>
<td>0.34</td>
<td>0.45</td>
<td>0.38</td>
<td>0.47</td>
<td>0.55</td>
</tr>
</tbody>
</table>

Standard errors in parentheses, clustered by industry. All regressions use sampling weights. *** p<0.01, ** p<0.05, * p<0.1
Creative Destruction? Startups and Divorce
Tünde Cserpes (Aarhus University), Michael S. Dahl (Aarhus University) and Olav Sorenson (Yale University)

Keywords: divorce, organizations, startups, bureaucracy, career alignment

Few would argue that organizations do not affect the personal lives of their employees. After all, the average adult spends more waking hours in the workplace than in any other setting. Yet, despite the prevalence of these accounts, systematic research on the effect of employers on the personal lives of their employees remains limited. To what extent do the demands of the workplace spill over into employees’ personal lives? We focus on divorce as a harbinger of the more general negative consequences of a stressful work environment and explore the relationship between organizational stability and the marital stability of employees.

Although a handful of contextual studies have considered the effect of employment on divorce, they have almost uniformly focused on the characteristics of the job rather than of the organization. In other words, these jobs have been disembodied from the firms that created them. When women earn more, for example, divorce rates increase (e.g., Oppenheimer 1997; Özcan and Breen 2012; Killewald 2016). Jobs that have been perceived as more satisfying, meanwhile, have been found to reduce reported levels of tension in the relationship (e.g., Hughes et al. 1992). But people who perceive their jobs as interfering with their family life report higher levels of marital discord and dissolution (e.g., Matthews et al. 1996; Presser 2000; Schneider and Harknett 2019). Although these studies suggest that organizations contribute to differences in divorce rates, they remain circumstantial evidence at best as they typically measure individuals’ attitudes towards their jobs rather than actual variation in organizational environments.

What has been missing from prior contextual studies of the relationship between employment and marital stability has been an organizational perspective, an understanding that structural features of the firm influence the nature of the jobs that employees hold and of the environments that they experience. Much as Baron and Bielby (1980) argued for bringing the firm back into the study of stratification, we would argue for a parallel introduction of the firm into the study of the work-family relationship.

Young organizations, startups, have traditionally been seen as attractive employers, offering more interesting jobs, better opportunities for individuals to advance their careers, and more supportive social environments (Campbell 2013; Roach and Sauermann 2015; Kim 2018; Sorenson et al. 2019). One might therefore expect their employees to have higher levels of life satisfaction and lower divorce rates. But startups also differ from more established firms in ways that may have negative effects on their employees as fledgling firms lack established roles and routines (Stinchcombe and March 1965). Employees must therefore navigate their jobs on a daily basis. Startups also frequently find themselves in financial duress and fail at high rates (Freeman et al. 1983; Yang and Aldrich 2017), meaning that their employees worry about the security of their employment, their income, and their personal finances (Roach and Sauermann 2010). These stresses may spill outside the organization into the home, elevating divorce rates.

Using Danish registry data, we explore empirically whether employees differ in their divorce rates as a function of the characteristics of their employers. Because we have at most one event per individual (or couple), we estimate single-event piece-wise exponential hazard models. We use the number of days from the time of marriage as the clock and split annual spells where appropriate to update time-varying variables.
To allow for an extremely flexible baseline relationship between the rate of the divorce and time in marriage, we include time pieces in our models for each year that has elapsed.

We find that workers in entrepreneurial ventures have the highest hazards of divorce. The gales of creative destruction noted by Schumpeter appear not only to sweep away incumbent organizations but also to erode marital bonds. This effect, moreover, does not appear to stem from selection on who sorts into startup employment and hold when using instrumental variables. But it does, interestingly, depend on the nature of the spouse’s employment. Couples employed in similar sorts of organizations have lower divorce rates, even when both members of a couple have jobs in startups. Our results therefore suggest that the organizational instability of employers spills over to create marital instability among their employees but also that couple-level factors – whether expectations of what the job entails or a tolerance for uncertainty – moderate these effects.

References


