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The dark side of employee mobility: Evidence from enterprise software adoption

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Abstract
While most academics agree that information technology (IT) has a positive impact on firm performance, performance differences between firms due to IT investments are quite large. One way to increase firm productivity when adopting IT is to hire experienced people. However, using a data set that links firm level data with individual level data, we empirically find that hiring experienced people drives decreases the performance of the firm. This suggests that learned practices that have proved successful in the former firm do not necessarily fit into the new firm.

Jelcodes:L86,M50

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Keywords: knowledge transfer, employee mobility, enterprise software, ERP, CRM

JEL Classification: L86, M50, O33

1. Introduction

IT adoption and its effect on the economy are so prevalent that some authors talk about a revolution which is larger than electricity (Jovanovic and Rousseau 2005). Even though the days of the Solow Paradox, when the pure existence of productivity increase through IT usage was questioned, are past, observed performance differences in IT adoption still remain largely unanswered.

We assess flows of IT-experienced workers between firms as one possibly important driver of performance differences in IT adoption. Transfer of experienced workers between firms is usually believed to have positive effects due to knowledge spillovers. Our core question is therefore whether a firm can learn through its new employees from other firms' IT experiences to improve IT performance? Or in other words: does hiring employees with IT experience make a difference in IT performance?

We try to find answers for this question in the empirical setting of enterprise resource planning (ERP) software adoption. ERP adoption is interesting in the context of organizational change and IT adoption as the implementation of ERP systems has a decisive impact on business processes and structures and thereby on employees. More specifically, we focus on one specific type of ERP systems: customer relationship management (CRM) systems.

We extend a classic Cobb-Douglas production function with lagged ERP adoption, an ERP experience measure of newly hired employees, and an interaction term of the two. When estimating the production function, we are especially interested in the interaction term, as this term tells us whether firms that have adopted an ERP system and have hired a high proportion of workers with prior IT experience are more successful.

Our unique data set stems from three sources. First, US data on ERP adoption is provided by Harte Hanks and has been widely used in IT productivity research (e.g. by Brynjolfsson and

Hitt 2003). Second, we merge financial data from Orbis. Third, we use data on individual career paths from the professional online network LinkedIn. Our final data-set consists of 5,696 firm-year observations between 2000 and 2008.

Our main result is surprising: along a wide range of specifications, we get consistently negative and significant coefficients for the interaction term of ERP adoption and ERP experience of newly hired workers. That is, ERP adoption is less successful, the higher the share of newly hired workers with prior ERP experience. A possible explanation for this result could be failed generalizations, i.e. learned practices that have proved successful in the past (in the former firm) do not necessarily fit into the new firm and consequently have adverse effects.

2. Related literature

We try to give answers to the question if knowledge transfer by employee mobility affects the success of technology adoption. We therefore motivate our study by reviewing two streams of related literature: while the first stream (section 2.1) deals with related literature on knowledge transfer by employee mobility, the second stream (section 2.2) deals with existing studies on performance implications of ERP adoption.

2.1. Knowledge transfer by employee mobility

In this paper, we evaluate the impact of knowledge transfer on the performance of enterprise software adoption. Knowledge transfer between firms happens when one firm's experience has an impact on other firms (Argote and Ingram, 2000). There are several mechanisms how this experience can be transmitted between firms. Reviewing the existing literature on knowledge transfer, Corredoira and Rosenkopf (2010) distinguish between strategic alliances, employee mobility, informal publications, patents, and scientific publications as potential mechanisms of knowledge transfer. Acknowledging the importance of other mechanisms of knowledge transfer, we focus on employee mobility as a possible way of transferring experience from one firm to another.

In his seminal work on the link between employee mobility and knowledge spillovers, Arrow (1962) stresses that information is a commodity of great economic value and that “the very use of information in any productive way is bound to reveal it”. Subsequently, mobility of employees will spread information and as property rights can only partially bar this, information therefore lacks appropriability. In environments with increasingly knowledge intense production, this effect is amplified, as the departing worker cannot leave everything behind due to the often tacit knowledge acquired from experiences at the workplace. The literature on R&D has taken up this thought line and interprets labor mobility as a spillover.[1] But it also has been argued that the transferred knowledge is compensated for by wage differences and therefore cannot be qualified as spillovers (Møen, 2005). As employees are able to transfer tacit and explicit knowledge to new contexts (Berry and Broadbent, 1984, 1987) and as they can adapt the transferred knowledge to these new contexts (Allen, 1977), we expect employee mobility to be a powerful mechanism of knowledge transfer (Argote and Ingram, 2000).

Empirical studies have found knowledge-enhancing effects from worker movement for the hiring firm[2]. Studies in the semiconductor industry observe hiring firms importing new product line strategies (Boeker, 1997) and technical knowledge (Rosenkopf and Almeida, 2003, Song et al., 2003), while studies in other industries observe increased product innovation (Rao and Drazin, 2002) and increased influence in technical committee activity (Dokko and Rosenkopf, 2010). Even though all these studies show support for a link between

[1] Therefore, insufficient appropriability of research investments may lead to underinvestment.
[2] In addition to the literature evaluating the impact of worker mobility on the hiring firm, Corredoira and Rosenkopf (2010) also evaluate the impact on the firm losing an employee and find a reverse channel of knowledge transfer from the new firm of an employee to their old firm. So knowledge transfer does not always have to lead to negative effects because of human capital losses, but can also have a positive effect because of social capital gains.

employee mobility and knowledge transfer, much less is known if this transferred knowledge is ultimately useful for the hiring firm, i.e. if hiring firms can increase profitability by employing the acquired knowledge. One exception is Phillipps (2002), who finds higher firm survival rates for law firms hiring new partners. While establishing important contributions to the understanding of organizational populations, firm performance is not observed directly, but by the coarse proxy of firm survival.

Our study adds to the existing literature on knowledge transfer in two dimensions. First, we are able to directly examine performance implications of knowledge transfer by employee mobility. And second, we identify how knowledge transfer influences the success of one specific adoption problem, the adoption of enterprise software. This second point is discussed in the following section.

2.2. Performance implications of ERP adoption

In the context of the IT revolution, software seems to be a much larger productivity driver than hardware. However, surprisingly few productivity studies analyze the impact of software compared to the vast majority of IT and productivity studies that mainly focus on hardware. Obviously, one possible reason for the smaller number of studies could stem from difficulties in quantifying software-capital, which speaks for looking at the adoption effect of software adoption instead.

In this paper, we consider enterprise resource planning (ERP) software as one specific but fairly important kind of software. While ERP adoption is generally seen as a profit-increasing strategy, many firms like Hewlett Packard or Hershey’s experience problems when adopting ERP systems.[3] This leads to some appeals that stress the risk of ERP software implementation and question its benefits altogether (Rettig, 2007). So what could drive benefits and costs of ERP adoption? An ERP system integrates fragmented information systems, simplifies data

[3] Compare http://www.cio.com/article/486284/10_Famous_ERP_Disasters_Dustups_and_Disappointments

flows, provides information at a higher update frequency, and ensures data quality due to its predetermined data structures. This should lead to improved planning capabilities, improved processes, and efficiency gains. However, all this comes at a cost. In addition to the licensing and implementation costs payable to the software vendor, firms need to redesign their job and work routines, retrain their employees in how to use the new system, and build interfaces to legacy systems. The net effect of adopting an ERP system therefore depends on achievable efficiency and coordination gains (Gattiker and Goodhue, 2005) and on the hurdles that have to be overcome to achieve a fit between the organization and the selected ERP system.

While some of the existing work on ERP adoption is case study based and looks at the mechanisms by which ERP can create value and questions surrounding the implementation process (e.g. Botta-Genoulaz and Millet (2006), who analyze six cases of ERP adoption in the service sector), we are especially interested in large-scale empirical studies. For example, Jones et al. (2011) measure performance of ERP adoption in 49 different business units by their impact on monthly sales and inventory turnover and conclude that one needs to focus on minimizing negative outcomes during the implementation phase of enterprise software. Gattiker and Goodhue (2005) find that integrated and dependent units within a firm will profit more from ERP adoption than more isolated and therefore organizationally different units. Engelstätter (2009) uses a production function approach to estimate the returns of ERP adoption and identifies complementarities when a firm adopts multiple functional modules. Other examples of empirical studies on ERP adoption are Shin (2006), who analyzes ERP adoption of small and medium-sized enterprises or Hendrickes et al. (2007), who investigate the effect of announcing the introduction of an ERP system on stock prices and profitability. The main drawback of the above-mentioned study is their cross-sectional nature, which makes identification of causal effects difficult.

The only econometric studies on ERP performance using panel data were carried out by Aral et al. (2006) and Hitt et al. (2002). Even though both use a sample that only contains data of one large ERP vendor (SAP) in the US, a remarkable advantage of their dataset is the possibility to distinguish the date of purchase of an enterprise system and the date of its first usage. Aral et al. (2006) use this specific information to address the causality issue of whether it is the productive firms investing in IT or the actual use of IT that triggers better performance. They find that the basic ERP purchase decision is uncorrelated with performance, indicating the absence of a selection effect of better firms. Though they do find the selection effect for additional IT purchases, firms that are successful in implementing ERP, i.e. show good IT performance, will rather invest in additional modules. Hitt et al. (2002) focus on looking at different performance measures and span the very early period of ERP diffusion (1986-1998), which makes their findings are confined to the first effects after ERP implementation. They find that most of the gains are already found during the official implementation stage, which has an average length of 21 months.

Our study contributes to the literature on enterprise software adoption by analyzing the performance implications of adopting ERP software with a large-scale panel dataset of US firms. Our data has the advantage that it does not stem from one provider of ERP software, but comes from a wave of site-level surveys on ERP adoption, therefore containing ERP adoption by any ERP supplier. Contrary to the above-cited literature, we are not so much interested in the adoption effect itself, but in how the success of ERP adoption is moderated by the inflow of knowledge from hiring new employees.

3. Identification of effects from knowledge transfers on the success of ERP adoption

In our empirical analysis, we try to identify effects from knowledge transfer by employee mobility on the success of adopting an ERP system.

Our analysis is based on the established production function. Starting point is the Cobb-Douglas production function $Q = AC^{\alpha_1}L^{\alpha_2}$, where Q is the total production, C and L stand for capital and labor and A being total factor productivity.

For our estimations, we use the familiar production function in log linear form, which has the advantage of being widely accepted and used in the literature (e.g. by Brynjolfsson and Hitt (1996), Black and Lynch (2001), or Francalanci and Galal (1998)) and has a simple functional form. Our baseline regression for panel data and with lagged ERP Adoption is:

$$\ln Q_{it} = \alpha_0 + \alpha_i + \alpha_y + \alpha_1 \ln C_{it} + \alpha_2 \ln L_{it} + \alpha_3 ERP_{i,t-1} +$$

For the first estimation equation, we use a lagged ERP adoption variable, which is a dummy variable that takes the value of one, if in the year before the firm had implemented an ERP. Furthermore, we have an intercept α_0, allow for firm-specific fixed effects α_i and control for nationwide shocks with year dummies α_y. To make the results more comparable to the results of Hitt et al. (2002), we run some estimations with industry fixed effects at the three digit NAICS level instead of firm fixed effects.

The model that tests our main research question extends this software production function by a variable capturing ERP experience of newly hired employees[4] $EXP_{i,t-1}$, and the interaction of this variable with the lagged adoption variable $ERP_{i,t-1}$:

$$\ln Q_{it} = \alpha_0 + \alpha_i + \alpha_y + \alpha_1 \ln C_{it} + \alpha_2 \ln L_{it} + \alpha_3 ERP_{i,t-1} + \alpha_4 EXP_{i,t-1} + \alpha_5 ERP_{i,t-1} EXP_{i,t-1}$$

When estimating the production function, we are especially interested in the interaction term, as this term tells us whether firms that have adopted an ERP system and have hired a high proportion of employees with prior IT experience are more successful.

[4] The exact implementation of the variables is discussed in section 4.2.

For all panel regressions we use robust standard errors, as the assumption of normally distributed idiosyncratic error term with mean zero is usually not met with panel data. Robust standard errors allow for the weaker assumption, that the errors only have to be independent across individuals (Cameron and Trivedi, 2009).

4. Data

4.1. Data sources

For the empirical analysis we draw data from three different sources.

For the information on enterprise software adoption we use the US issue of the CI Technology Database provided by the international marketing and information company Harte Hanks. This database has been used extensively by academic literature on IT productivity research (Bresnahan et al., 2002, Brynjolfsson and Hitt, 2003), but is primarily collected for commercial purposes for large IT companies and its quality is therefore regularly tested and established. The data stems from yearly telephone surveys at a firm's site level and contains amongst other measures of IT usage detailed information on the employed software. To allow for linking the data with financial data and firm level data of worker flows, we aggregate the information on a firm level using a corporation identifier provided by Harte Hanks.

Data on worker flows between firms comes from the public directory of LinkedIn, which is the market leader for professional online social networks, capturing a significant portion of white-collar workers in the US. Professionals use the LinkedIn network amongst others to connect to business contacts, search for new jobs, and to acquire new customers. Users of LinkedIn fill out a structured online resume containing their employment history and education. Figure 1 depicts an exemplary profile from LinkedIn's public directory. The employment history contains information on start and end date of the employment, on the employer, and of the job title of the employee. We can therefore track employee movement between firms on an individual level. Micro-level data from LinkedIn has been used by Tambe and Hitt (forthcoming) to estimate IT productivity.[5] They compare their analyzed sample on IT employees with data from the Bureau of Labour Statistics and find the data to be representative and to cover about 10-15% of the US based IT workforce.[6]

INSERT FIGURE 1 HERE

Finally, we complement our data on IT usage and worker flows with financial data from the Orbis database provided by Bureau van Dijk. As most studies using financial data, there is a bias towards large firms in the sample. This is a cost that comes with using this kind of data, but one has to keep this in mind when interpreting the data. This holds especially true as increasingly smaller firms start adopting ERP systems.

Matching between the datasets was done by firstly firm name, secondly industry, and third headquarters location as this information was available in all three datasets. After applying an automatic matching process, each matched firm was manually checked for correctness. Due to the double-checking of matched firms the matched quality should be very high.

4.2. Variables

In the following, we introduce the variables used in our estimations. Descriptive statistics are presented in Table 1, while pairwise correlations are reported in Table 2.

[5] They do not explicitly state that their data comes from LinkedIn, but LinkedIn is the only professional network of comparable site that has been active in the US at this time.
[6] Our data sample differs in the vintage of the data acquisition (2010 instead of 2006), in that we only use publicly available date from the LinkedIn members directory, and that we use all kind of workers instead of only IT workers.

4.2.1 Value added

Our dependent variable, value added ($Q_{i,t}$), is measured as sales minus costs. Material costs are reported only for few firms in the dataset and in order to avoid losing a great number of observations, we use data from the Bureau of Economic Analysis to calculate the average material spending in percent of output for each industry at the three digit NAICS level.[7] Individual material costs for each firm are imputed from taking the industry percentage from the actual reported sales. Not surprisingly the calculated data are strongly correlated with the available material costs data. Even though this is an imperfect substitute, for this applied case of looking at CRM software (which has a main focus on sales instead of material cost reduction such as supply chain management), this is a sufficient approximation for the production function. The regressions were repeated with sales instead of the value added proxy as dependent variable and results and significance remained unchanged.

4.2.2 Adoption of ERP software

In our empirical analysis, we focus on the adoption of one specific type of ERP systems, i.e. customer relationship management (CRM) systems. The variable $ERP_{i.t}$ takes a value of one if a firm i has adopted a CRM system in year t and a value of zero otherwise. Of course, firms can implement ERP systems in many different ways: adoption can differ regarding the number of sites, licenses, modules (even within the field of CRM-ERP), and the number of employees using the software. We interpret this as a random data error in our adoption measure, which will tend to bias our results toward finding no effect (Hitt et al., 2002).

CRM systems are used for all tasks relating to the interface with the customer. For example, they allow for sales force automation, they simplify maintaining long-term relationships, and they enable centralized customer data warehousing, which in turn can lead to improved profiling of key customers. Furthermore, they allow for better analysis of customer

[7] Data is accessible at http://www.bea.gov/industry/gdpbyind_data.htm

profitability and purchasing patterns, especially if a firm has multiple product lines. So the goal when implementing a CRM-ERP is to achieve superior customer loyalty and to reduce costs of sale. CRM systems usually replace systems maintained by individual sales people and prevent the loss of organizational customer knowledge with sales people turnover (Hendricks et al., 2007). Finally, repetitive sales processes can be streamlined. The best known CRM vendors are Oracle, Peoplesoft, and Siebel (Shin, 2006), though the last two have both been bought by Oracle in 2004 and 2005 respectively. Further important players on the CRM market are Salesforce.com and SAP.

Figure 2 shows the diffusion curve for CRM software in the US. The level of adoption is higher for manufacturing, which is not very surprising given that ERP software was originally primarily targeted at the manufacturing sector. Growth of the diffusion curve across the sectors is synchronous. We study the adoption of CRM systems instead of general-purpose ERP systems as their main adoption window falls in our study period, whereas overall ERP adoption has already been much more saturated throughout the study period.

INSERT FIGURE 2 HERE

4.2.3 Experience inflow

Our central variable $EXP_{i,t}$ measures the inflow of ERP-specific experience and is constructed as the ratio of new employees of firm i recorded at LinkedIn with prior experience with an ERP-CRM software denominated by the number of a firm i's all new employees recorded at LinkedIn. This variable gives information on the degree to which experience with the specific software is present within the newly recruited employees, but it gives no information on the extent of newly recruited employees in relation to the total labor force, i.e. on labor turnover.

The measure is constructed as a stock variable in the sense that once a new employee with ERP experience is counted, she is counted every year until she leaves the firm. This makes sense as her knowledge of her prior experience does not extinguish after her first year in the new company and the experience of coming in from another firms can be interpreted as a stock variable.

Constructing this variable as a ratio instead of constructing a variable using absolute terms, i.e. number of employees, is due to, firstly, correcting the variable by different sampling rates will always run into a selection problem and, secondly, the percentage variable can be interpreted very sensibly.

4.2.4 Control variables

Finally, to be able to estimate the production function we need variables on capital and labor. Capital $C_{i,t}$ is measured as the fixed capital employed by firm i in year t, whereas labor $L_{i,t}$ is measured as the number of full-time equivalent employees of firm i in year t. Furthermore, we construct a set of year dummies α_y to control for nationwide shocks influencing productivity. Finally, for our preferred regressions, we use a set of firm-level fixed effects α_i, for some robustness checks we use industry fixed effects at the three digit NAICS level.

INSERT TABLE 1 HERE

INSERT TABLE 2 HERE

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5. Results

5.1. Main findings

Our main findings are presented in Table 3. In this table, we run regressions with fixed effects at the level of the firm. First off, the coefficients for intercept (multifactor productivity), labor and capital are in their usual ranges.

INSERT TABLE 3 HERE

In our specification (1), we find a positive stand-alone effect from lagged ERP adoption, but this effect is statistically not significant. The main effect for ERP adoption becomes only significant in specifications (2) and (3), when we control for ERP experience and the interaction between experience and adoption. It is reassuring to find that the experience inflow variable on its own has no effect on productivity. Which shows that the inflow of ERP experienced employees does not in any way show a bias towards selection of good or bad employees, but only has an effect if combined with an ERP system at the firm.

In contrast to the expected positive coefficients for the interaction terms between ERP experience and ERP adoption, we find significant negative coefficients. This unexpected and at a first glance counterintuitive result holds true for lagged (specification (2)) as well as for contemporaneous measures of ERP experience (specification (3)).

5.2. Robustness checks

To allow for better comparability with the existing ERP productivity literature (Hitt et al., 2002), we rerun the regression with industry controls at the three digit NAICS level instead of firm fixed effects. Results are reported in Table 4.

INSERT TABLE 4 HERE

It is interesting to see how much the results change when one changes from regressions with firm-level fixed effects to industry controls. Even though the direction of all variables stays the same, differences occur in the significance of the results. For example, the stand-alone effect of ERP adoption is now significantly positive (specification (1)). A possible explanation could be causality problems for the industry control framework: if a firm is generally more productive, it might adopt an ERP system. As long as general productivity differences between firms are not time-variant, this reverse causality problem can be taken care of by the fixed effects regression. In contrast, the interaction term of ERP adoption and experience stays negative but in no longer significant.

We also applied the same regression estimation and models from Table 3 on the manufacturing sector only. We do this mainly because a large part of the IT productivity literature is focused on this sector and one argument is that the accounting data is more reliable for manufacturing than in the service sector. For example, the accuracy of accounting data in the finance sector has been questioned. In other service sectors, such as the as the health sector, severe quality issues at the output level exist. Results are reported in Table 5 and are similar to using the full available data set.

INSERT TABLE 5 HERE

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6. Discussion

Our empirical analysis produced a counterintuitive and unexpected main result: along a wide range of specifications, we get consistently negative and significant coefficients for the interaction term of ERP adoption and ERP experience of newly hired workers. That is, ERP adoption is less successful, the higher the share of newly hired workers with prior ERP experience. In the following, we try to identify possible mechanisms that could have generated this result.

A first possible explanation could be that wage premiums of ERP-experienced employees could drive this result. The line of thought here would be that ERP-experienced employees could be able to realize higher wages than inexperienced employees and that these wage premiums outweigh their potential efficiency gains, leading to a negative net effect on productivity. However, we only get a significantly negative effect for the interaction term of experience and ERP adoption and not for the main effect of experience. If employees with ERP experience would "overcharge" their employers, we would expect a negative effect even more for the main effect than for the interaction term, as it captures the contribution of ERP-experienced employees to productivity for the case when they are not even able to bring in their knowledge.

A second possible explanation would be a story of reverse causality: perhaps those firms that experience problems with their ERP adoption hire a larger share of ERP-experienced employees? If this would be the case, the negative interaction effect of ERP adoption and ERP experience would just indicate firms with low capabilities of implementing an ERP system and not a negative influence of hiring a large portion of ERP-experienced employees. However, we think we can exclude this explanation as our measure of experience inflow is lagged and as the firm fixed effect already capture if a firm has an inherently lower capability of implementing an ERP system.

Third, the effect could possibly be explained with the diffusion of CRM systems. As over time more and more firms adopt a CRM system, the chance of hiring a new employee with ERP experience increases ceteris paribus. If over time ERP adoption would become less and less successful, a spurious correlation between ERP experience and time could explain our result. We think we can also exclude this possible explanation as our year fixed effects should control for a general upward trend in ERP experience. Furthermore, given that learning curves should usually generate positive effects, a generally reduced adoption success over time seems not to be very realistic.

Fourth, results could potentially be explained by the substitution of internal and external knowledge. Implementation of ERP projects is usually supported by a large-scale involvement of external consultants. These consultants usually have long-time experience with implementing ERP systems and should be able to deal with most problems during the implementation phase. A high percentage of newly hired employees with ERP experience could be an indicator that a firm tries to manage the implementation process with fewer external consultants and with more internal resources. Therefore, we could explain the negative interaction effect between internal ERP experience and ERP adoption if external knowledge provided by consultants would be more efficient than internal resources. We think this mechanism could potentially drive our results. However, consultants are usually only active in the implementation phase of the project and leave thereafter. As we also regard long-term success of ERP adoption, we think that performance differentials of external and internal knowledge can only explain a smaller part of the overall effect.

Fifth and finally, another explanation could be transfer of wrong knowledge. ERP systems are complex systems that require a good fit with a firm's organizational structure. Employees with ERP experience could already observe such a fit between software and organization at their prior employer. However, given the high complexity of organizations as well as of ERP software, this fit should be fairly unique for each firm adopting an ERP system. So the question to be asked is if employees are able to successfully transfer knowledge from their old firm to their new firm? As Argote and Ingram (2000) argue, knowledge transfer can only be successful if the knowledge fits also in the new context. So success of knowledge transfer depends on whether employees with ERP experience are able to transfer real knowledge from one firm to another or if they are only able to copy a more or less static configuration. If they take their old firm's ERP configuration as a template of how to employ ERP software in the new firm, odds are high that no high performance can be achieved and that results are even worse than those for inexperienced employees as these employees should not have any bias for or against a specific configuration. We therefore think that transfer of wrong knowledge could in fact be a mechanism driving our negative interaction term between ERP adoption and ERP experience.

7. Conclusion

In this paper, we tried to assess the influence of knowledge transfer by employee mobility on the success of adopting complex enterprise software. Using a uniquely compiled dataset on ERP adoption, employee movement, and firm productivity, we were able to directly assess the moderating effect of employee movement on ERP adoption.

We expected to observe a positive effect from knowledge transfer on the success of adopting new ERP software. However, our main result goes in the opposite way: the higher the share of new employees with ERP experience, the lower the success of ERP adoption. We tried to make sense of this counterintuitive result by exploring potential mechanisms triggering the result. We could exclude wage premiums of ERP experience, reverse causality, and spurious correlations because of the diffusion process as possible mechanisms. While we identified employment of external consultants as a possible smaller driver of the result, our main line of explanation has been motivated by transfer of "wrong" knowledge: learned practices that have proved successful in the past (in the former firm) do not necessarily fit into the new firm and consequently have adverse effects.

Even though we are quite confident that our negative effect from knowledge transfer on the success of ERP adoption exists, we still cannot clearly identify the mechanisms driving the results. To allow for a better identification of the causal mechanisms, it would therefore be helpful to run a couple of additional tests. First, one such test could distinguish employee inflow from the same industry from employee inflow from different industries to test if knowledge acquired in a subject field closer to the new subject field could be transferred easier. If we would get this result, the explanation by "wrong" knowledge transfers would be supported, as knowledge would only become more "wrong" the more distant the old context would compared to the new firm. Second, it would be informative to use the duration of employment at the old employer as a proxy for an employee's knowledge rigidity and depth. In this context, it would be informative to see whether inflowing employees with longer prior experience contribute more because of their increased knowledge depth or less because of their higher rigidity. Third, it would be interesting to distinguish if the inflowing knowledge comes mainly from one firm or from many different firms. On the one hand, knowledge inflow from one firm could have the drawback that not so many new ideas are brought into the process and solutions get stuck on "local peaks" (Levinthal, 1997). On the other hand, knowledge inflow from many different sources could also turn out to be detrimental as knowledge integration becomes difficult (Grant, 1996).

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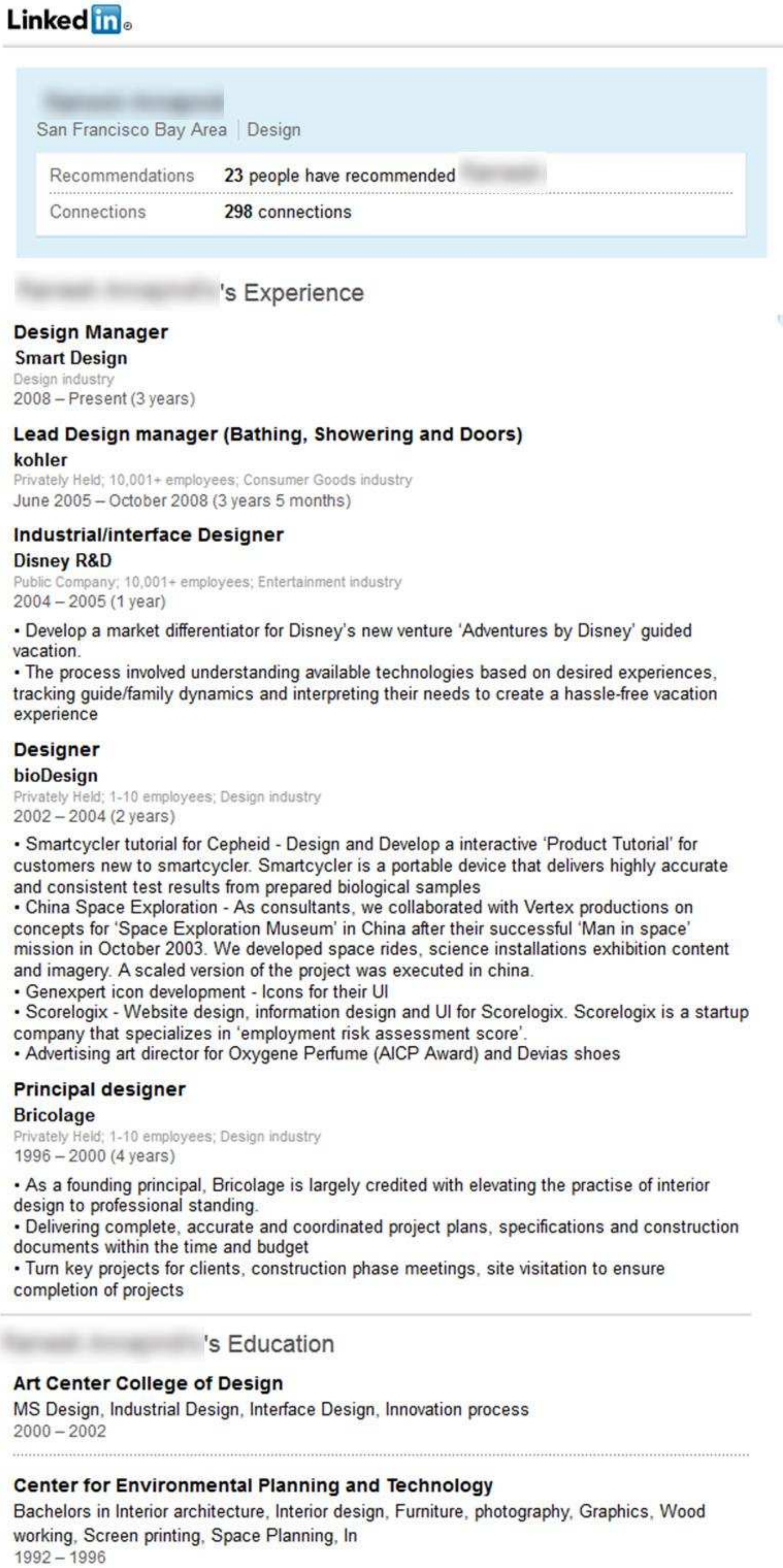
Figures and tables

Figure 1: Example profile from LinkedIn's public directory



San Francisco Bay Area | Design

Recommendations 23 people have recommended

Connections 298 connections

's Experience

Design Manager
Smart Design
Design industry
2008 – Present (3 years)

Lead Design manager (Bathing, Showering and Doors)
kohler
Privately Held; 10,001+ employees; Consumer Goods industry
June 2005 – October 2008 (3 years 5 months)

Industrial/interface Designer
Disney R&D
Public Company; 10,001+ employees; Entertainment industry
2004 – 2005 (1 year)

• Develop a market differentiator for Disney's new venture 'Adventures by Disney' guided vacation.
• The process involved understanding available technologies based on desired experiences, tracking guide/family dynamics and interpreting their needs to create a hassle-free vacation experience

Designer
bioDesign
Privately Held; 1-10 employees; Design industry
2002 – 2004 (2 years)

• Smartcycler tutorial for Cepheid - Design and Develop a interactive 'Product Tutorial' for customers new to smartcycler. Smartcycler is a portable device that delivers highly accurate and consistent test results from prepared biological samples
• China Space Exploration - As consultants, we collaborated with Vertex productions on concepts for 'Space Exploration Museum' in China after their successful 'Man in space' mission in October 2003. We developed space rides, science installations exhibition content and imagery. A scaled version of the project was executed in china.
• Genexpert icon development - Icons for their UI
• Scorelogix - Website design, information design and UI for Scorelogix. Scorelogix is a startup company that specializes in 'employment risk assessment score'.
• Advertising art director for Oxygene Perfume (AICP Award) and Devias shoes

Principal designer
Bricolage
Privately Held; 1-10 employees; Design industry
1996 – 2000 (4 years)

• As a founding principal, Bricolage is largely credited with elevating the practise of interior design to professional standing.
• Delivering complete, accurate and coordinated project plans, specifications and construction documents within the time and budget
• Turn key projects for clients, construction phase meetings, site visitation to ensure completion of projects

's Education

Art Center College of Design
MS Design, Industrial Design, Interface Design, Innovation process
2000 – 2002

Center for Environmental Planning and Technology
Bachelors in Interior architecture, Interior design, Furniture, photography, Graphics, Wood working, Screen printing, Space Planning, In
1992 – 1996

Figure 2: Adoption of CRM systems in the US

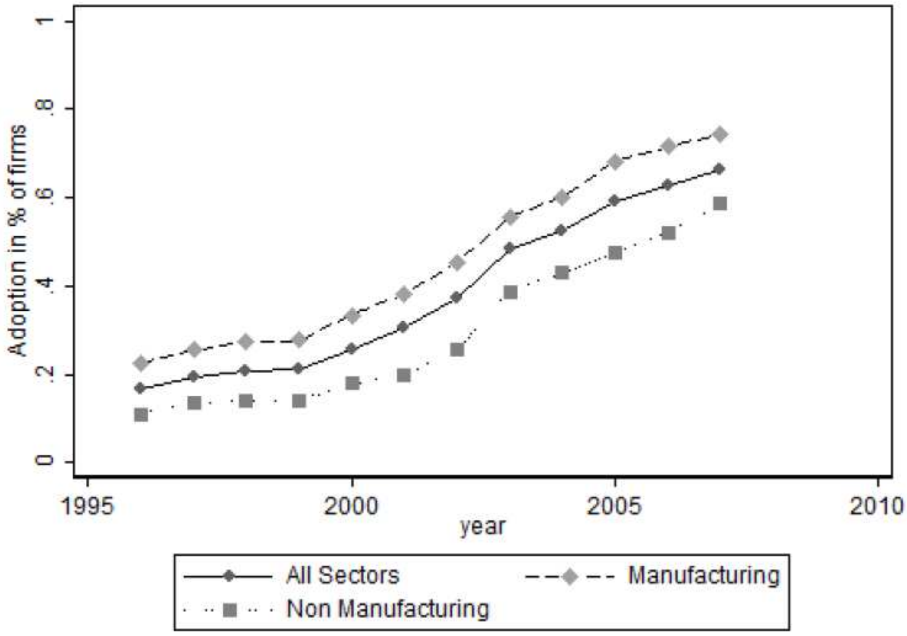


Table 1: Descriptive statistics

Variable	Obs	Mean	Std. Dev.	Min	Max
Value Added in 100000 USD	5696	4316	15000	3432	366000
Fixed Assets in 100000 USD	5696	5182	16300	0.467	251000
Employees	5696	21119	74965.51	15	2100000
ERP CRM Adoption	5696	0.526	0.499	0	1
ERP CRM Experience in % of Worker Inflow	5017	0.443	0.178	0	1

Table 2: Pairwise correlations

	Value Added	Fixed Capital	Employees	Year	EXP
Fixed Capital	0.6623				
	(0.0000)				
Employees	0.8445	0.4686			
	(0.0000)	(0.0000)			
Year	0.0257	0.0117	-0.0079		
	(0.0685)	(0.4083)	(0.5778)		
EXP	0.0028	-0.0151	-0.0022	0.4400	
ERP-CRM experience in %	(0.8436)	(0.2839)	(0.8769)	(0.0000)	
ERP	0.0674	0.0859	0.0646	0.2526	0.2421
Adoption of ERP-CRM Software	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)

Notes: Numbers each display pairwise correlation coefficients. Numbers in parenthesis report significance level

Table 3: Main regressions results with firm fixed effects

	(1)	(2)	(3)
Dependent Variable	Value Added	Value Added	Value Added
$\mathbf{ERP_{t-1}}$	0.007	0.060**	0.073**
Adoption of ERP-CRM Software	(0.014)	(0.030)	(0.035)
$\mathbf{EXP_{t-1}}$		0.050	
ERP-CRM Experience Inflow in %		(0.059)	
$\mathbf{EXP_{t}}$			0.046
ERP-CRM Experience Inflow in %			(0.070)
$\mathbf{ERP_{t-1} * EXP_{t-1}}$		-0.135**	
Interaction of Adoption and Inflow		(0.063)	
$\mathbf{ERP_{t-1} * EXP_{t}}$			-0.151**
Interaction of Adoption and Inflow			(0.071)
$\mathbf{ln(C)}$	0.189***	0.194***	0.194***
Fixed Capital	(0.019)	(0.019)	(0.019)
$\mathbf{ln(L)}$	0.452***	0.439***	0.439***
Employees	(0.036)	(0.036)	(0.036)
Constant	7.184***	7.633***	7.632***
	(0.212)	(0.228)	(0.229)
Year Controls	Yes	Yes	Yes
Observations	5,696	5,017	5,020
Number of Firms	1,027	914	915
R-squared	0.813	0.809	0.809

Notes: Fixed-effects (within) regression estimation. Each column is a separate regression which distinguishes itself through the variables and lags included. The time period is 2000-2008, containing data from the US. Hubert-White robust sandwich standard errors are in parentheses. Significance levels are *** $p<0.01$, ** $p<0.05$, * $p<0.10$. R-squared for overall model. See text for more details.

Table 4: Regression results with industry fixed effects

	(1)	(2)	(3)
Dependent Variable	Value Added	Value Added	Value Added
$\mathbf{ERP_{t-1}}$	0.080*	0.120**	
Adoption of ERP-CRM Software		(0.043)	(0.050)
$\mathbf{EXP_{t-1}}$		-0.014	
ERP-CRM experience in %		(0.084)	
$\mathbf{EXP_{t}}$			0.080
ERP-CRM experience in %			(0.096)
$\mathbf{ERP_{t-1} * EXP_{t-1}}$		-0.113	
Interaction of Adoption and Inflow		(0.081)	
$\mathbf{ERP_{t-1} * EXP_{t}}$			-0.187**
Interaction of Adoption and Inflow			(0.092)
$\mathbf{ln(C)}$	0.170***	0.169***	0.168***
Fixed Capital	(0.025)	(0.025)	(0.025)
$\mathbf{ln(L)}$	0.494***	0.495***	0.494***
Employees	(0.044)	(0.045)	(0.046)
Constant	7.452***	7.252***	7.233***
	(0.274)	(0.308)	(0.308)
Year Controls	Yes	Yes	Yes
Observations	3,175	2,795	2,798
Number of Firms	496	442	443
R-squared	0.689	0.676	0.676

Notes: Fixed-effects (within) regression estimation. Each column is a separate regression which distinguishes itself through the variables and lags included. The time period is 2000-2008, containing data from the US. Hubert-White robust sandwich standard errors are in parentheses. Significance levels are *** p<0.01, ** p<0.05, * p<0.10. R-squared for overall model.

Table 5: Regression results for manufacturing

	(1)	(2)	(3)
Dependent Variable	Value Added	Value Added	Value Added
$\mathbf{ERP_{t-1}}$	0.080*	0.120**	
Adoption of ERP-CRM Software		(0.043)	(0.050)
$\mathbf{EXP_{t-1}}$		-0.014	
ERP-CRM experience in %		(0.084)	
$\mathbf{EXP_{t}}$			0.080
ERP-CRM experience in %			(0.096)
$\mathbf{ERP_{t-1} * EXP_{t-1}}$		-0.113	
Interaction of Adoption and Inflow		(0.081)	
$\mathbf{ERP_{t-1} * EXP_{t}}$			-0.187**
Interaction of Adoption and Inflow			(0.092)
ln(C)	0.170***	0.169***	0.168***
Fixed Capital	(0.025)	(0.025)	(0.025)
ln(L)	0.494***	0.495***	0.494***
Employees	(0.044)	(0.045)	(0.046)
Constant	7.452***	7.252***	7.233***
	(0.274)	(0.308)	(0.308)
Year Controls	Yes	Yes	Yes
Observations	3,175	2,795	2,798
Number of Firms	496	442	443
R-squared	0.689	0.676	0.676

Notes: Fixed-effects (within) regression estimation. Each column is a separate regression which distinguishes itself through the variables and lags included. The time period is 2000-2008, containing data from the US. Hubert-White robust sandwich standard errors are in parentheses. Significance levels are *** p<0.01, ** p<0.05, * p<0.10. R-squared for overall model.