Peer Effects, Free-Riding and Team Diversity*

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Abstract

We estimate the effects of peer contemporary and peer permanent productivity to understand if behavior at the workplace is affected by point-in-time performance or a high/low productivity signal. We exploit unique field panel data on cargo warehouse agents consolidating freight onto pallets with the help of a forklift. Shift composition is haphazard and team size of up to 20 agents depends on export demand. We find evidence for both types of peer effects only in teams with more than 9 agents: agents free-ride when working with high permanent-productivity peers whereas they increase performance when working with high current-productivity agents. By estimating heterogeneous effects we find that free-riding is highest when all peers belong to the nationality that comprises the majority and has on average the highest permanent productivity. Moreover, agents consider peers' point-in-time performance to be more important than peers' permanent productivity. In order to exploit efficiently the benefits of peer contemporary effects, production should take place only in large enough teams with sufficient diversity in nationality backgrounds.

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1 Introduction

We estimate peer contemporary and peer permanent productivity effects in order to understand if behavior at the workplace is affected by point-in-time performance or a fixed high/low productivity signal. An agent with high (low) permanent productivity (Mas and Moretti, 2009) might temporarily experience irregularities so that for certain shifts performance is much lower (higher) than expected. Peers might perceive the deviation between the realized and the expected performance. The question we pose is: Do agents react to peer current productivity, to peer permanent productivity, or to both? To answer this question, we use unique field panel data from a cargo company on warehouse agents who consolidate freight items on cargo pallets with the help of a forklift. The institutional and legal setting allows us to obtain clean identification of both types of peer effects. The deviation between current and permanent productivity is real: In 55% of hourly shifts, the agent with the highest ability is not the one with the highest current productivity. While in small teams peer effects are absent (see Steinbach and Tatsi, 2016), in large teams agents respond to both peer current and permanent productivity. The two effects work in opposite directions: A 10% increase in peer current productivity increases own productivity by 6.5% whereas a 10% increase in peer permanent productivity decreases own productivity by 0.78%. By estimating heterogeneous effects in large teams we find that free-riding is highest when all peers belong to the nationality that comprises the majority and has on average the highest permanent productivity: a 10% increase in peer permanent productivity decreases own productivity by 2.23%. The latter underpins the role of identity and culture in economic outcomes (Kreps, 1990; Akerlof and Kranton, 2000, 2005): Individuals with shared backgrounds have similar behavioral tendencies. We view this result as an empirical example of Kets and Sandroni (2016) who show that team homogeneity in terms of identity and culture reduces strategic uncertainty and agents get locked in an inefficient Nash equilibrium. As the overall peer effect is positive (see also Steinbach and Tatsi, 2016), we conclude that agents consider peer current performance to be more important than peer permanent productivity.

The studies of Steinbach and Tatsi (2016) and Steinbach (2016), examine peer effects among warehouse agents who work in a group production process at a freight forwarding company. Comparing agents working alone and in the presence of others, Steinbach and Tatsi (2016) uncover the existence of general peer effects (team differential) and highlight the importance of team size and spatial proximity for the emergence of social effects. Steinbach (2016) finds that these social effects are not driven by compositional peer pressure among agents on a general level: An increasing average ability of one's peers does not influence own effort.[1] In general, peer permanent productivity effects cannot explain the social effects in the given setting – a result not line with studies conducted in similar settings (e.g., Mas and Moretti, 2009) and raises the question what other behavioral channel is driving the social effects found by Steinbach and Tatsi (2016). Additionally, both studies find remarkable heterogeneity in agents' responsiveness to the presence of others and make an educated guess about the emergence of free-riding (as a consequence of partially negative

[1] Only an increase in the permanent productivity of the lowest able peer in a shift leads to a ceteris paribus increase in one's own current productivity. This is related to last-place aversion.

effects) among obtained workers.

Peer effects occur in the form of endogenous (contemporaneous or current) and exogenous (contextual) effects. Both current behavior as well as peer characteristics may influence a focal agent's current output. Mas and Moretti (2009, p. 121) with reference to peer contemporaneous and peer permanent productivity state that "[...] *both forces could be at play at the same time"*. Steinbach and Tatsi (2016) as well as Steinbach (2016) do not answer the question whether and—if so—to what extent a worker's current output is influenced by the current output of his colleagues. The only exceptions at the workplace are the studies by Horrace, Liu, and Patacchini (2016) and Lindquist, Sauermann, and Zenou (2015). In this paper, we uncover the *whole* social effect and disentangle peer current working behavior from peer characteristics such as permanent productivity. The data are perfectly suited for studying social interactions: we observe individual performances of 320 warehouse agents[2] who build up freight pallets with the help of forklifts and barcode scanners (see Figures 4.4 and 4.8). The process takes place in four large warehouse halls, each of a size of around $4,000$ square meters. The period of observation is 45 months (January 2011 – September 2014). Managers who schedule shifts have asymmetric information on individual agent productivity while team size as well as tasks depend exogenously on export demand. Furthermore, laws protecting workers' rights prohibit employment of the same high (low) productivity agents in high (low) demand periods. Therefore, hourly shift compositions are formed unsystematically and endogenous sorting can be ruled out. Agents gain a fixed wage and their efforts in the build-up activity are perfectly substitutable so that estimated coefficients actually reflect the effect of working in the presence of others.

We define a general peer effects model which accommodates agents' characteristics as well as both endogenous (average peer current productivity) and exogenous social effects (average peer permanent productivity and characteristics). We exploit two sources of variation to identify parameters: team size variation and variation in team composition within a Saturday or an hourly shift.[3] Then, we estimate multiple nested specifications of the general peer effects model: first, we estimate a rather general model taking into account the characteristics of the focal worker and his peers (contextual effects without peers' permanent productivity). Second, we estimate a model with respect to the average permanent productivity of one's peers. This type of model refers to permanent productivity effects and is similar to Mas and Moretti (2009) and Steinbach (2016). Then, we also include own and peers' characteristics. Third, we estimate a model which allows own performance to depend on the average peer current productivity. This type of model examines endogenous effects. In an enhanced version, we control for own and peers' characteristics. Finally, we estimate a model accounting for all determining factors, in parallel: peer average permanent

[2] The initial data set covers 335 warehouse agents. In our analysis, we focus on Saturday observations. 15 agents are not observed on a Saturday. Consequently, they are excluded.

[3] For identification of endogenous social effects, see – for cross-sectional data – Lee (2007) for interactions in a group context with group fixed effects, Davezies, D'Haultfoeuille, and Fougére (2009) for group interactions with missing values and group fixed effects, Bramoullé, Djebbari, and Fortin (2009) for interactions in groups or networks with group or network fixed effects, respectively, and – for panel data – Horrace, Liu, and Patacchini (2016) for interactions in groups with individual and time fixed effects.

productivity, peer average current productivity as well as own and peer average characteristics in the hourly shift. The latter model reflects our preferred specification as it refers to endogenous and exogenous effects. The regressions of the first two specifications are estimated via OLS, the other two via 2SLS. As instruments, we use the characteristics of the peers of one's peers.[4] All four models include controls for spatial aspects and time patterns and, therefore, take into consideration correlated effects. To obtain possible differences in the manifestation of effects with respect to group sizes (as suggested by Steinbach and Tatsi, 2016), we estimate all specification forms, first, for the whole sample, second, for team sizes of 3 to 9 agents (small teams), and, third, for team sizes of 10 or more agents (large teams).

The results herein have important implications for managerial policies. Often, literature postulates positive peer effects as a substitute for incomplete financial incentives that are typical in employment relationships (e.g., Kandel and Lazear, 1992; Mas and Moretti, 2009; Guryan, Kroft, and Notowidigdo, 2009). Our analysis, however, reveals that the optimal exploitation of peer effects is a challenging managerial task as endogenous and exogenous effects operate adversely and superpose each other. Additionally, their dependence on team size is a challenging factor. Our findings suggest focusing on contemporaneous effects over permanent productivity effects as their contribution to individual output is larger. However, permanent ability must not be neglected. In general, organizations must aim to exploit the positive side of contemporaneous effects, and concurrently avoid consequences through possible negative impacts. As a major implication, first, managers should compose large shifts with employees who have not worked together often because peer permanent productivity effects are negative. If employees do not know each other's ability signal, then the remaining effect is the positive effect coming from peer current productivity. In a nutshell, not knowing peers' ability signal makes agents more productive. We could have not inferred this result by exploring peer permanent or peer current productivity effects alone. In a setting where workers know coworker ability and feel comfortable enough around each other to free-ride, the introduction of a fast-working newcomer countervails free-riding: average current productivity increases (without changing workers' perception of average peer permanent productivity) and so does individual productivity because of the positive endogenous social interactions. Contemporaneous group behavior is more powerful than long-term behavior measured by permanent productivity. Second, managers should compose teams with diverse nationalities. Free-riding is maximum when all peers have the same nationality. Sharing the same culture and language creates a working environment where free-riding is deemed as a socially acceptable behavior.

Our findings present a different view on the meaning of contemporaneous and long-run behavioral group influences. We demonstrate the interplay of endogenous and contextual effects and elucidate consequences when abstracting from one type of peer effects. From a practical point of view, we believe our results are broadly applicable—especially to related production environments. With

[4] Note that our model does not suffer from the reflection problem because, instead of using a linear-in-*expectations* model including the outcome of the focal worker in the expectation (Manski, 1993), we specify a linear-in-*means* model excluding the productivity of the focal worker from the mean (for the endogenous effect). To overcome the problem of endogeneity, we estimate via 2SLS using the characteristics of one's peers' peers as instruments (see Lee 2007; Bramoullé, Djebbari, and Fortin 2009; Lee and Yu 2014; Boucher, Bramoullé, Djebbari, and Fortin 2014).

regard to employment, the transport and logistics sector (in which our study is conducted in) is the third largest branch in Germany. It follows the automotive and retail sector. Around three million people (which corresponds to 1.2 percent of the German labor force) work in transport and logistics (BVL, 2015; DSLV, 2015; Destatis, 2015; Kille, Schwemmer, and Reichenauer, 2015). Moreover, many firms in the global economy operate comparable team-production settings and may face similar effects (for instance, catering, retail industry, or automotive production).

This rest of paper is organized as follows. The subsequent Section presents a broad overview of the peer-effects literature. Section 3 discusses why it is crucial to uncover both types of peer effects, endogenous and exogenous and why management has to know whether contemporaneous or long-term group behavior is driving individual productivity. Section 4 refers to the production environment, the measure of productivity, the role of workers and managers as well as the incentive scheme. Section 5 describes the data. We present our econometric framework in Section 6 and the corresponding estimation results in Section 7. The last Section concludes.

2 Literature Review

There is a long list of literature on peer effects, and scientific work goes back to the end of the 19th century. First, Triplett (1898) provided evidence on the idea that an individual's performance might be affected by others. Comparing cyclists' race times he found that athletes were faster under competition, and slower when racing against the clock. These findings are abstracted with the term *social facilitation*.[5] The author argued that the mere presence of other subjects has a positive effect on one's own performance caused by subjects' intrinsic competitive drives: That is, performance might be *facilitated*.[6] In contrast, other studies prove that an individual's performance might also be lowered by the presence of others (Allport, 1924; Husband, 1931; Pessin, 1933; Jackson and Williams, 1985; Karau and Williams, 2008). Peer effects, in general, can be either positive or negative. Zajonc (1965) theorizes that these opposed effects result from the variety concerning a task's complexity: While for simple or well-practiced tasks the mere presence of others enhances productivity, for complex and difficult tasks the presence of others may inhibit performance.

The set of empirical studies examining peer effects in a workplace environment increased during the last decades. Other favored domains of examination are education (e.g., Jackson and Bruegmann, 2009; Calvó-Armengol, Patacchini, and Zenou, 2009; Sacerdote, 2001; Burke and Sass, 2013; Boucher, Bramoullé, Djebbari, and Fortin, 2014; Booij, Leuven, and Oosterbeek, 2017), sports (e.g., Triplett, 1898; Gneezy and Rustichini, 2004; Guryan, Kroft, and Notowidigdo, 2009; Gould

[5] The term social facilitation was coined by Allport (1924).

[6] In studies on maze-solving and run races, Gneezy, Niederle, and Rustichini (2003) and Gneezy and Rustichini (2004), respectively, concretize these results finding that males are more competitive than females. In the latter study, the authors report young males running faster when competing against another young male compared to when running alone. Analyzing car drivers, Palat and Delhomme (2016) also present evidence on behavioral effects through the presence of others: Among other things, the authors find subjects stop later at a yellow traffic light when they could perceive other drivers whose driving behavior was conducive to yellow-light running compared to when there was no social influence. Even if the participants stopped at a yellow light, the presence of others made them accelerate faster when the signal switched from red to green, again.

and Kaplan, 2011; Yamane and Hayashi, 2015; Arcidiacono, Kinsler, and Price, 2017), science (e.g., Azoulay, Zivin, and Wang, 2010; Rawlings and McFarland, 2011; Waldinger, 2012), crime (e.g., Glaeser, Sacerdote, and Scheinkman, 1996; Gould and Kaplan, 2011), shirking (e.g., Ichino and Maggi, 2000; Bradley, Green, and Leeves, 2009), traffic (e.g., Palat and Delhomme, 2016), sales (e.g., Aakvik, Hansen, and Torsvik, 2013; Chan, Li, and Pierce, 2004) and production (e.g., Hamilton, Nickerson, and Owan, 2003; Falk and Ichino, 2006; Kato and Shu, 2008; Mas and Moretti, 2009; Guryan, Kroft, and Notowidigdo, 2009; Bandiera, Barankay, and Rasul, 2010; Kaur, Kremer, and Mullainathan, 2015; Amodio and Martinez-Carrasco, 2015; Georganas, Tonin, and Vlassopoulos, 2015; Lindquist, Sauermann, and Zenou, 2015; Cornelissen, Dustmann, and Schoenberg, 2017). Note that this list is not exhaustive. Since we focus on applied empirical research, a detailed description of any of these articles would go beyond the scope of this paper. Hence, we subsequently provide summaries of selected articles and studies which we assess to be known when dealing with peer effects in the workplace.

Falk and Ichino (2006) present one of the first studies on peer effects in a work-like environment. In a lab setting, students were asked to fill letters into envelopes in exchange for a fix payment. In the so-called "single treatment" students work alone, and there is no potential for the occurrence of peer effects. In the "pair treatment" two students work independently on the task sitting in the same room, and peer effects are possible. The authors provide evidence on the existence of positive peer effects in two ways: First, individuals' outputs in the "pair treatment" significantly exceed individuals' outputs in the "single treatment". Second, a comparison of outputs variances indicates that subjects under teamwork are more similar in their production behavior compared to when working alone. In their experiment, low-productive students react most sensitive to their peer's behavior.

Mas and Moretti (2009) examine peer permanent productivity effects in a real workplace setting. By using individual data on the productivity of supermarket cashiers they verify peer effects which appear as productivity spillovers caused by social pressure.[7] At first sight, these findings seem surprising because the underlying working process is expected to be prone to free-riding: Individual output is not exactly observable by managers and cashiers are paid fixed wages and therefore are independent of coworkers' performances—for a cashier it seems rational to unload one's workload onto his coworkers. However, the possibility of mutually monitoring each other's output causes positive peer effects for observable workers. Cashiers react on emerging social pressure of their observers through enhancing their current productivity. In this specific setting, peer effects countervail the incentive to free-ride, because they may internalize some of the externalities that are typical for this kind of team-production processes. Moreover, the authors find that peer-effect magnitudes are large for low-skilled workers and small for high-skilled workers. To investigate the generalizability of these results, van Veldhuizen, Oosterbeek, and Sonnemans (2014) conduct a lab experiment reflecting the setting and the production features from Mas and Moretti (2009). In their study, they explicitly control for various aspects to rule out alternative social and non-social channels which

[7] Kandel and Lazear (1992) theorize the concept of social pressure and its influencing potential on workers' production behavior.

may influence a worker's productivity. The authors also find evidence on the existence of peer effects. However, within their experiment, peer effects operate differently. In particular, they find a larger heterogeneity in the magnitude of peer effects among workers, and peer effects can be even negative: Whereas some workers increase their productivity in the presence of a more productive coworker, others tend to free-ride. Comparing real work productivities of data-entry agents sitting next to each other, the field study of Kaur, Kremer, and Mullainathan (2015) also provides evidence on the existence of peer effects emerging as productivity spillovers through social pressure.

By exploiting individual data on defect rates of weavers working for a textile manufacturer, Kato and Shu (2008) verify the existence of peer permanent productivity effects in their setting as well. In this production environment, peer effects are caused by performance spillovers through unidirectional knowledge sharing from high-ability weavers to low-ability weavers. In a subsequent working paper, the authors additionally show that the weavers' performance is positively influenced when interacting with more productive out-group peers but not when interacting with more productive in-group peers. They prove that inter-group competition can be a further possible source for peer effects in the workplace (Kato and Shu, 2009).

Bandiera, Barankay, and Rasul (2010) combine individual performance data with data on friendship relations among fruit pickers of an agricultural firm who work under a relative incentive scheme. The authors also find evidence on peer effects in the form that one's output is affected by the average output of his peers: In the absence of externalities from incentive schemes or production technologies, workers tend to conform to the productivity level of their friends when mutual monitoring is possible. Low-productivity workers increase their effort when working with more able friends. In contrast, high-productivity friends lower their exerted efforts when producing with less able friends, thereby forgoing up to 10% of their own salaries. In general, the net effect is positive.

The majority of related field studies focuses on the estimation of contextual peer effects. So far, only very few papers estimated contemporaneous peer effects in the workplace. In a recent paper, Lindquist, Sauermann, and Zenou (2015) exploit panel data on individual outputs of call-center agents working in quasi-random teams for a mobile network operator. By creating a weighted graph on within-team interaction frequencies among workers, the authors provide evidence on the existence of contemporaneous peer effects among coworkers. These effects operate through the worker network of the firm. A 10% increase in the current output of an agent's coworker network results in a 1.7% increase in the focal agent's current output. The productivity spillovers are driven by the group's average performance. Agents with low tenure are most sensitive in their reactions to the productivity level of their coworker network. Horrace, Liu, and Patacchini (2016) also estimate contemporaneous peer effects in a workplace-like environment. In their approach, they specify a network model that incorporates contemporaneous peer effects on worker productivities and apply it to a dataset on individual performances of players of a college basketball team. The authors report positive contemporaneous productivity effects across players in the same category (offensive or defensive) but no significant effects across players in different categories. An increase in the average current performance of other active offensive (defensive) players leads to a 0.05 unit increase in the current performance of the focal offensive (defensive) player.

Guryan, Kroft, and Notowidigdo (2009) use random groupings of elite golf players to test whether peer effects exist in the context of professional golf tournaments. Within their setting, peer effects are not present. Waldinger (2012), who analyses a dataset on the historical research performance of natural scientists, also finds no evidence for peer effects (within a researcher's department) [8]—even the best researchers do not affect the output of their peers. Cornelissen, Dustmann, and Schoenberg (2017) provide further insights on these different findings. Using a large panel on workers and firms in a local labor market the authors show that peer effects not only lead to spillovers in productivity but also to (albeit moderate) spillovers in wages. Additionally, they find that both peer effect magnitudes as well as channels depend on a job's complexity: Peer effects are small in innovative and high-skilled tasks (for which knowledge spillovers are expected to be important) and large for low-skilled and repetitive tasks (where outcomes are observable and workers can easily evaluate their peers' performance).[9] While some papers provide evidence on the existence of peer effects (both positive and negative), others do not find significant results. In their meta-study on the comparison of peer-effect magnitudes on worker outputs, Herbst and Mas (2015) provide an overview about 34 relevant papers—thereof 23 field studies and 11 laboratory experiments. The authors calculate that the average estimate of a change in a worker's productivity in response to a ceteris paribus increase in his peers' productivities is significantly positive ($\bar{\lambda} = 0.12$). They also report several studies with negative peer-effect estimates. Emergence, magnitude and type of potential peer effects in real workplace settings vary across individuals, working environments, task complexity and incentive schemes.

Turning to the econometrics literature, during the last years we have witnessed advances with reference to social interactions (e.g., Davezies, D'Haultfoeuille, and Fougére 2009; Bramoullé, Djebbari, and Fortin 2009; Goldsmith-Pinkham and Imbens 2013; Johnsson and Moon 2017; de Paula, Rasul, and Souza 2017), and especially in the spatial econometrics strand (e.g., Kelejian and Prucha 1998; Lee 2003; Kelejian, Prucha, and Yuzefovich 2006; Lee 2007; Lee, Liu, and Lin 2010; Liu and Lee 2010; Liu 2014; Tao and Lee 2014; Hsieh and Lee 2014; Horrace, Liu, and Patacchini 2016; Cohen-Cole, Liu, and Zenou 2017). In our empirical exercise, we exploit a spatial autoregressive type model to estimate the simultaneous effect of coworker productivity, i.e., the Nash equilibrium in a simultaneous peer effects game (Calvó-Armengol, Patacchini, and Zenou, 2009), along with the coworker permanent productivity effect and other contextual effects. To our knowledge, this is the first study to shed light on the complex nature of peer effects: is it the endogenous or the exogenous social interactions that matter? Is it peer permanent or peer current productivity that matters?

[8] Focusing on supra-regional collaborations, Waldinger (2012) verifies that losing a coauthor is negatively related to one's own scientific productivity.

[9] These findings support the hypothesis of Zajonc (1965).

3 Economic Relevance and Motivation

Empirical studies on peer effects in the workplace focus exclusively on the estimation of *one* type of peer effects (in most cases, the exogenous type; only in a few cases the endogenous type). But social effects can be driven through both endogenous and exogenous forces. By only examining one type, the entire social effect cannot be uncovered precisely and managers have no information whether contemporaneous or long-term group behavior influences individual effort. Moreover, one may attribute wrong meanings to a single effect type leading to incorrect economic conclusions. Analyzing warehouse agents consolidating freight pallets, Steinbach and Tatsi (2016) find that agents are more productive when working in a team than when working alone. This differential is attributed to general social effects. Steinbach (2016) verifies that these social effects cannot be explained by the mean ability of one's peers.[10] It becomes obvious, that only looking at one specific type of peer effects is not sufficient.

Peer current productivity and peer permanent productivity are different measures of performance. As an example, imagine an agent who is known to be highly productive—that is, he has a high permanent productivity. Assume that he temporarily experiences private problems, and, thus, performs much lower than expected for certain shifts. His peers perceive his productivity to be lower than the (expected) permanent performance (i.e., they perceive a deviation). The yet unanswered question is, do his peers react to his current productivity, to his permanent productivity, or both? And if they do, in what way? The answer is relevant, for instance, for composing shifts optimally: If managers know whether to bring together employees who know each other's low or high ability signal (permanent productivity), they can enhance team outputs. As a further example, consider a worker l working with a highly able colleague m who, however, performs worse always when working with l but not with other peers—because m dislikes l. Under some circumstances, workers may perform badly although they have a high permanent productivity. Looking at our data, we find that in around 55% of all observed hourly shifts the worker with the highest ability is not the one with the highest current productivity in the shift. Permanent and current productivity can deviate substantially in certain shifts.

Another point to mention is that permanent productivity effects only arise when workers know each other's ability. When working together only for a few minutes with a certain coworker, one would not be able to evaluate whether his peer is of high or low ability—that is, a certain number of interactions is necessary before compositional forces can arise. Compared to endogenous effects, for permanent productivity effects a high degree of information is required as colleagues have to know about each other's permanent productivities. In many working environments, this is not given, especially when new workers arrive or when shift compositions change permanently. For endogenous effects, this kind of knowledge is not necessary because workers can determine coworker current productivity "at first sight" (without prior knowledge).[11] The necessity of disentangling both effect

[10] Steinbach (2016) rather suspects tendencies for free-riding if the average permanent productivity of one's colleagues increases.

[11] Besides endogenous and permanent productivity effects, managers and organizations also have to know about further contextual effects to obtain the whole picture on social workplace interactions—that is, the influence of one's

types becomes even more important if endogenous and exogenous effects operate adversely (i.e., one effect is positive and the other one negative). Then, managers have to shut down the negative channel accordingly (e.g., to avoid free-riding) while exploiting the positive one. This task can be quite complex. However, if the manager knows exactly about the influence of both short-term and long-term group behavior, he can deduct appropriate measures to enhance team production.

A distinction of these peer-effect types is important for a further reason: Endogenous effects may operate throughout the whole network having the potential for multiplier effects through the feedback of affected workers—for example, positive working behavior leads to more positive behavior in the network (Hoxby, 2000; Lindquist, Sauermann, and Zenou, 2015). Contextual peer effects, in contrast, do not come along with such dynamic implications (Bobonis and Finan, 2006). By definition, permanent productivity effects are covered by contextual effects since they are featured to be caused through the exogenous characteristics of one's peers (Manski, 1993). In this paper, we extract the compositional share with respect to peers' average permanent productivity from the "remaining" contextual effect. Overall, we disentangle endogenous effects and contextual effects and we also control for correlated effects. Note that similar to permanent productivity effects, "remaining" contextual effects, which result from one's peers characteristics, are not (always) instantaneously perceivable—that is, information accuracy is a function of interaction frequency.

4 Working Environment

In this Section we briefly describe the production setting, the working process, the incentive scheme and the measure of productivity for our empirical application.

4.1 Production Process

Warehouse agents consolidate freight items onto cargo loading devices (pallets). Typical freight items are car parts, motor parts, electronic parts, general spare parts, etc., which are packaged, for example, in robust cartons or boxes. The observation period is from January 2011 until September 2014 (45 months). Operations take place in a large warehouse with four identical halls. Each hall has a working space of around $4,000\text{m}^2$. Figure 4.1 depicts the footprint of the warehouse, Figure 4.2 one of the warehouse halls and Figure 4.3 pallets in line before the build-up procedure. Based on a pallet-specific build-up plan, warehouse agents consecutively pick up designated shipment items[12] with a forklift (see Figure 4.4) and load them onto a build-up unit. The corresponding shipment items are already procured in front of the designated pallets before the build-up starts. Usually, warehouse agents build up pallets simultaneously. In $10,874$ out of $83,091$ single build-ups (i.e., around 13%), more than one warehouse agent works on one and the same build-up unit. This is not an issue for measuring productivity since agents' efforts are not multiplicative but substitutable: Workers have no possibility to exploit complementarities in order to achieve a higher level of output

coworkers' characteristics as, for instance, gender, age, or nationality on own current productivity.

[12] A shipment is a set of items (pieces) with the same or similar properties.

compared to their peers under joint production. As a example, consider two warehouse agents who are building two pallets, A and B. Two process alternatives exist: First, each agent works on one separate pallet alone. Second, both agents jointly build up pallet A and pallet B, subsequently. Since efforts are substitutable, the productivities of the two agents and, hence, the overall build-up duration, are identical for both alternatives. There are no complementarities of joint work.

Figure 4.1: Warehouse Footprint (Simplified).

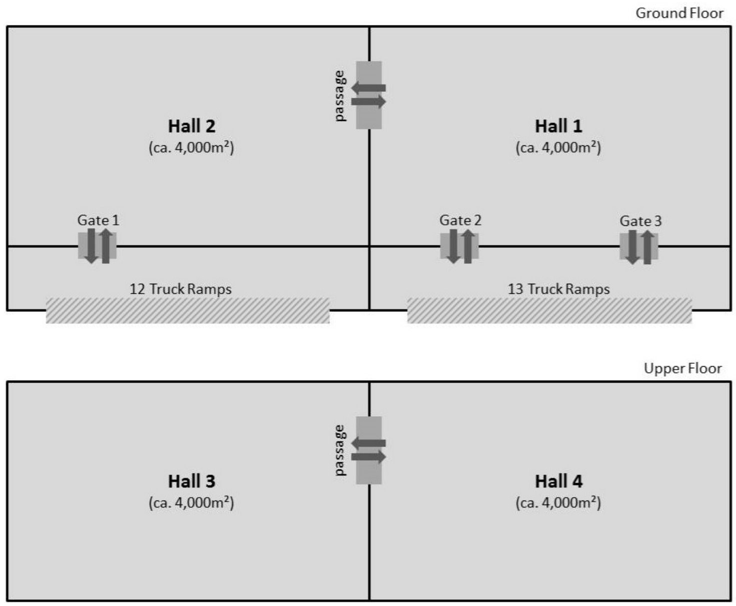


Figure 4.2: Warehouse Hall

Figure 4.3: Pallets in Warehouse Area

Figure 4.4: Forklift (exemplary).

Demand is a function of time. The weekly demand patterns are equivalently repetitive over the entire observation period. For each date we calculate the number of observations. Figure 4.5 graphs the average daily observations as well as daily observations for the bottom and top quantiles from the full sample with 335 agents, $41,421$ hourly shifts (warehouse hall$\times$hourly interval) in $23,029$ hours and $1,302$ days of consolidation. The average number of observations is highest for Saturdays (around 260 observations) followed by Wednesdays (around 110 observations). In fact, around 43% of the observations belong to Saturday. We do not observe production every day of the week and every team size (see Figure 4.6) or warehouse hall (see Figure 4.7). Production in larger team sizes corresponds to higher demand periods, i.e., Saturdays. When demand is relatively low consolidation procedures are performed only in hall 1 which is located closely to the export truck ramps where the freight is unloaded (see Figure 4.1). With rising demand, other halls are additionally utilized. Highest demand for consolidation procedures occurs on Saturdays between 7:00 and 17:00 when production occurs continuously (no dead time) and under all possible team sizes. This is because the to-be consolidated shipment items are produced by manufacturers during the working week and shipped directly thereafter. By gathering several freight during the working week, forwarders (offering the transport service for the manufacturer) realize scale effects with regard to transport costs and reduce the consolidation price rate. Hence, forwarders seek to ship the freight “batch-wisely” on Friday afternoon and Saturday morning leading to the obtained consolidation peak on Saturday. Also note that in Germany truck transports are not allowed on Sunday from 0:00 am until 10:00 pm due to legal prohibition.

Figure 4.5: Weekly Demand Pattern

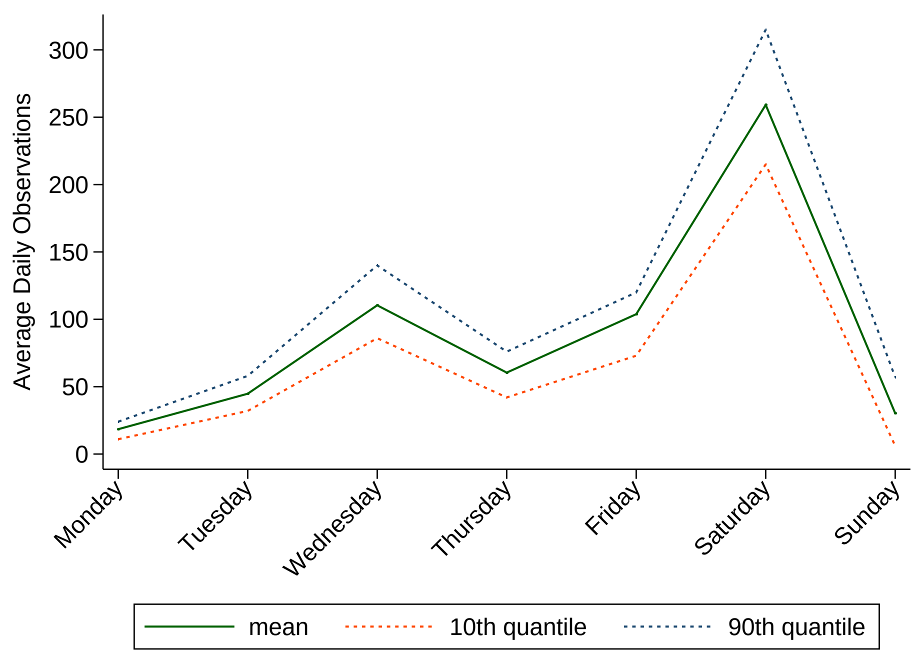


Figure 4.6: Number of Hourly Shifts by Team Size and Day of Week

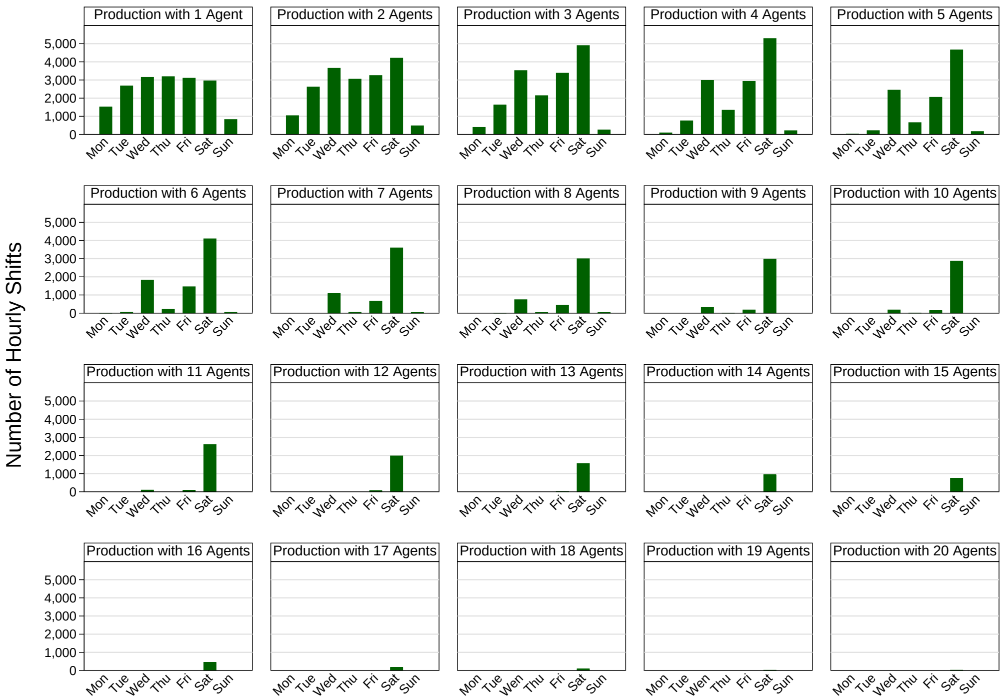
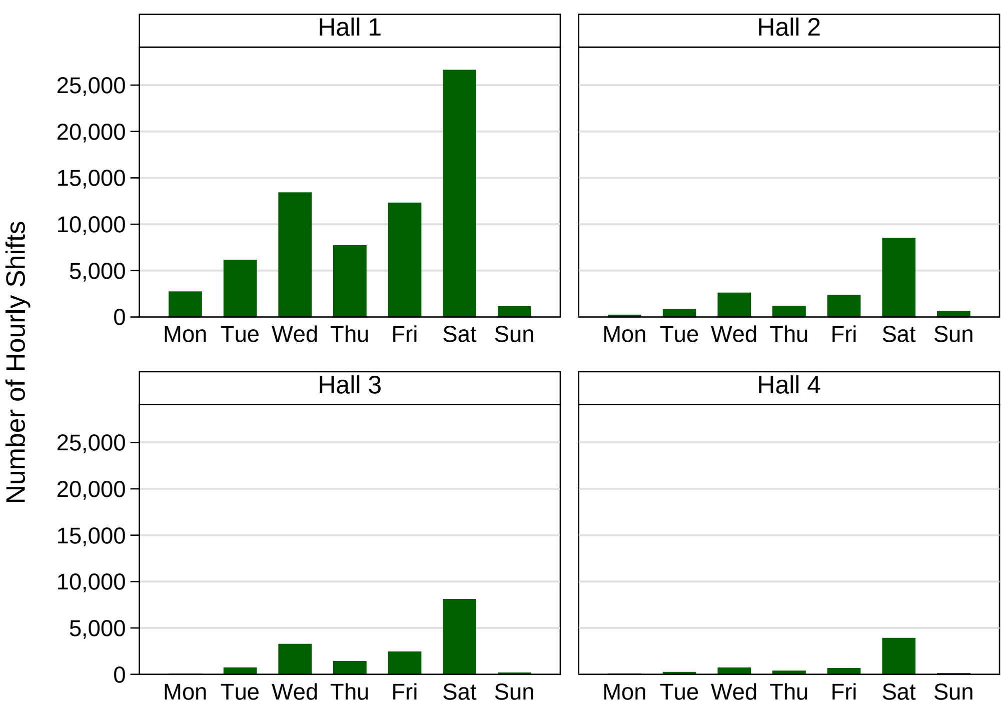


Figure 4.7: Number of Hourly Shifts per Day and Warehouse Hall



All movements of shipment items (e.g., from one warehouse location to another, into a truck, or onto a pallet) are captured by barcode scanners (see Figure 4.8) for which each agent uses a personal log-in. Transactions are consistently stored in the corresponding database of the warehouse management system. To process a build-up, the warehouse agents picks up a freight item, lifts it onto its designated pallet, and maneuvers it in the right position. Then, he confirms the procedure by scanning the pallet number and the shipment's barcode. In cases when he lifts more than one piece of a shipment, he additionally captures the number of built-up pieces (e.g., he lifts several small packets which are shrink-wrapped collectively). When all pre-planned items are loaded onto the pallet, the scanner prompts a dialogue to inform the agent that the build-up pallet is finalized. If a warehouse agent assigns a shipment item to a wrong pallet, the barcode scanner prompts an error dialogue. That is, assignments of items to wrong pallets are prevented by the warehouse management system and misroutings of shipments (to the wrong destination) can, thus, also be prevented. After the build-up is finished, the pallet is covered with a net, lashed with ties (see Figure 4.9), and prepared for the further transport - usually by other workers.

Figure 4.8: Barcode Scanner (exemplary).

Figure 4.9: Finished Pallet

In forwarder business, the consolidation process is seen as the most crucial activity because it is subject to high time pressure: While freight delivery for a certain pallet usually takes several days, the consolidation process itself has to be performed within a few hours (and often within less than 30 minutes) because – according to regulations – consolidations start when the majority of planned shipment items have been delivered and agreed safety measures as well as ordered extra services (e.g., sorting, shrink wrapping, etc.) are completed. As contracted with shippers and forwarders, the latest acceptance time of an export shipment is 120 minutes for standard freight and 30 minutes for express freight before the estimated build-up completion (which itself is strictly determined by the transport schedule of the supply-chain successor).[13] In practice, shipment delivery is often completed only minutes before the latest acceptance time since supply-chain members seek to minimize their overall cycle time. Hence, the consolidation process is well-suited for the empirical research on peer effects because time pressure is highest for involved participants: While late orders, unpunctual shipment deliveries or not-in-time processed extra services can be probably compensated by the overall warehousing process, a late build-up will irrevocably lead to an offload of the whole pallet (and, hence, each associated shipment item) from its designated outgoing transport vehicle. Not only the affected shipment items have to be replanned and rebooked on other successor transports by sales department but also transport planning (e.g., the capacity steering) has to be adjusted on short notice. Moreover, an offload may lead to contract penalties, and result in a damage to the company's image. The organization is a member of a worldwide association and has to publish

[13] Actually, contracts contain the requirement to deliver standard freight 180 minutes and express freight 90 minutes before the departure of the outbound transport vehicle. The organization calculates 60 minutes (loading and transport time) between build-up completion (pallet finalization) and the departure of outbound transport vehicle.

its quality performance indicators on a monthly basis to allow a public comparison with industrial competitors: Every offload has a negative influence on reported quality.

Compared to tasks like stuffing letters into envelopes (Falk and Ichino, 2006), picking fruits (Bandiera, Barankay, and Rasul, 2010), weaving cloths (Kato and Shu, 2008) or scanning items in a supermarket (Mas and Moretti, 2009), the considered build-up process for pallet consolidations is special due to two reasons: First, the exigencies on precision, accuracy and correctness of the tasks' outputs are very high since security guidelines are strict. Second, the task is complex: From a theoretical point of view, pallet consolidations can be interpreted as an enhanced *Bin Packing Problem*[14] with constraints imposing above average requirements on agents' combinatorial ability and working experience.

4.2 Measure of Productivity

The cargo company granted us access to anonymized, high-frequency and long-time performance data (pallet build-ups) on an individual level. The responsible warehouse agent captures each movement of a shipment item with the help of a barcode scanner. The warehouse management software stores historically all scanner transactions in a database.

Individual performance is precisely captured through three performance measures on an hourly basis: the number of build-up-barcode scans, the number of consolidated shipment items (pieces) and the weight of consolidated shipment items in kilograms. The corresponding variables are highly correlated as shown in Table 4.1. We use the number of build-up scans as the leading performance measure because it reflects individual performance best: after every forklift-build-up procedure, an agent scans the appropriate shipments' barcodes. Hence, the number of build-up scans is the main productivity driver for warehouse agents with regard to the forklift consolidation activity. Also, the number of consolidated pieces is a good performance measure since the volume and contour of a piece drive individual performance as well; for example, the number of single forklift procedures required to finish a build-up pallet depends on the characteristics of the single pieces. However, since more than one piece could be built up with one single forklift procedure, it may abstract from an agent's individual performance to some extend. For the build-up forklift procedure, the weight of consolidated pieces is of secondary relevance: for example, the consolidation of a 10 kilograms shipment item does not necessarily require more effort than the consolidation of a 300 kilograms shipment item).[15]

[14] The Bin Packing Problem is an optimization problem: Out of a given set of $i = 1..n$ items, each with a weight w_i and a volume v_i, those items have to be chosen for packing into a finite number of $j = 1..m$ containers (or bins), each with a weight capacity W_j and a volume capacity V_j, in a way that minimizes the overall number of used containers (Martello and Toth, 1990).

[15] The warehouse management software operates on shipment-level data. A shipment describes a freight entity of a single forwarder and consists of several (to be precise, one or more) pieces. For consolidations, warehouse agents are not forced to perform barcode scans of single pieces. Rather, they scan the shipment barcode and enter the number of related pieces with the help of the scanner keyboard to finalize the transaction. The data for a shipment's weight comes from its booking and is captured for the whole shipment. To approximate the weight of a single piece the software assumes an equal distribution of the weight across all shipment pieces (e.g., the weight of one piece of a shipment with 5 pieces and 100kg is expected to be 20kg).

Table 4.1: Correlation between Performance Measures

Variable	Build-Up Scans	Build-Up Pieces	Build-Up Weight (kg)
Number of Build-Up Scans	1		
Number of Build-Up Pieces	0.715	1	
Sum of Build-Up Weight (kg)	0.800	0.543	1
Number of Observations		108,668	

All performance measures are observable and comparable for a single warehouse agent over time, and comparable across different warehouse agents within one period and over time. The data are precise and collected on a worker-specific level: since every warehouse agent has his/her own scanner sign-in, there is a valid linkage between an item-movement transaction and the executing warehouse agent. All transactions are stored in the database of the warehouse management software without gaps. Hence, it is easy to identify (changes in) current individual productivities. By using this type of data we can also access information about shift compositions and the individual build-up contribution of each shift-group member. Because movements of shipment items are documented by a highly available software and requirements of security guidelines are strict, we expect measurement errors to be rare.

4.3 Role of Managers

The warehouse agents are employed by different organizations. For each organization, a manager schedules shifts four to six weeks in prior. Managers have no information on the agents' individual performances as they neither have access to the individual output data nor observe them during work. Managers do not participate in the consolidation process. Their offices are located in other parts of the building (for some managers, even in a different building). Group production is performed only by the agents. Besides their planning responsibility for build-up operations, they are involved in further activities as security, sales, controlling, customer relationship management, and so forth.

4.4 Shift Scheduling

Production is performed 24/7, and operations are organized in shifts work. In the current context, the term *work shift* represents a whole working shift with a duration of 8.5 hours (breaks included). The term *hourly shift*, however, describes a one-hour period t specific to a warehouse hall h where agent interactions are plausible. Each day, four work shifts are planned. Contracted service regulations define work-shift specific core time periods from 6:00 am until 2:30 pm in the early work shift, from 2:00 pm until 10:30 pm in the late work shift, and from 10:00 pm until 6:30 am (next day) in the night work shift. Moreover, there is a day work shift from 09:30 am till 06:00 pm in which only a few warehouse agents are planned for. From the defined core times it becomes obvious that work shifts overlap for at least 30 minutes. Thereby, appropriate hand over of information to successor work-shift colleagues and the maintaining of operations without interruptions can be ensured. Commonly, overlapping periods are longer than 30 minutes. Because working contracts allow for flexible working time, warehouse agents exploit the possibility to work overtime or to reduce long hours. In peak periods overlapping extends up to two hours.

Management is responsible for scheduling, and planning takes place several weeks in advance. Scheduling is haphazard, since the institutional setting does not allow for systematic assignment of workers into both work shifts and build-up shifts. Coworker compositions change permanently - there are no fixed teams. Additionally, the number of warehouse agents operating in working shifts and build-up shifts changes. On the one hand, work-shift compositions depend on the availability of colleagues, which is restricted by negotiated free-time regulations and vacation rules as well as other forms of absenteeism, e.g., due to illness and trainings. On the other hand, working-shift size is planned on the basis of expected demand (which is considered to be exogenous as described in Subsection 4.1). Management has no ambition to assign the most productive warehouse agents to the busiest work shifts. Warehouse agents do not only work in build-up operations during a working shift. They also process other tasks as loading trucks, unloading trucks, storing or relocating shipment items and breaking down import freight pallets. Hence, they are not always active in build-up procedures but in other activities, although the build-up process is the first priority in the warehouse. Agents log-in with their personal ID to the IT system (desktop, tablets and barcode scanners) to get information on the next tasks. Another source of team variation are staff changes through rotations within the firm, hires and job quits. All these facts lead to a very high degree of variation in shift compositions and shift sizes regarding the underlying time unit for the panel observations, i.e., the one-hour-time-interval. Table 4.2 summarizes the sources of variations leading to unsystematic compositions of shifts with respect to a one-hour-time-interval at the build-up activity.

We observe $24,002$ different shift compositions. We tag particular build-up-team constellations with the help of the historical database records of the warehouse agents' performances (i.e., time stamps are provided for each build-up transaction).[16] In Table 4.3 we report the frequency of observing an identical shift composition. The probability to observe one and the same shift constellation only once is around 84.7%. The probability to observe one and the same team composition for more than 7 times is smaller than 2.0%; for more than 17 times, it is smaller than 1% (c.f. Table 4.3). Recall that operations are observed from January 2011 until September 2014. This implies that within a time period of almost 4 years one and the same worker composition does not repeat for more than 17 times with a probability of around 99%. Hence, assuming a haphazard shift composition is reasonable, and sorting can be ruled out, accordingly. In Section 5.2 we test whether shift composition is indeed unsystematic.

[16]Besides inferring information about build-up shift compositions, we can also deduct the individual build-up contribution of each active warehouse agent.

Table 4.2: Sources of Variation in Build-Up-Shift Compositions.

No.	Source of Variation
1	Management has no information on individual productivities of their workers. There exist multiple managers who schedule work shifts independently. Managers are not present in build-ups.
2	Working shift size is determined exogenously by demand, and management has no ambition to assign most productive workers to the busiest shifts.
3	Laws protecting workers' rights prohibit the employment of the same potentially high-productivity worker, for instance, every Saturday when demand meets its peak.
4	Each day, four working shifts operate. Up to three shifts overlap simultaneously within a one-hour-time interval (e.g., at 02:00 pm, early, late, and day work shift overlap).
5	Due to illnesses and trainings, workers may be absent.
6	During the observational time frame, staff changes occur – through within-firm rotations, hires and job quits.
7	Warehouse agents operate in six different activities exogenously depending on activity-related demand: truck loading, truck unloading, storing, relocating, consolidating (build-up), deconsolidating (break downs).
8	Agents do not choose their work/hourly shifts or tasks. Agents log-in with their personal ID to the IT system (desktop, tablets and barcode scanners) to get information on next tasks. After security and safety, consolidation is top-priority in the warehouse.
9	Agents have contracted possibilities to work overtime or to reduce long hours.

Table 4.3: Relative and Cumulative Frequencies of Identical Shift Constellations.

Frequency of observing the same team composition	Relative proportion	Cumulative proportion
1	84.69 %	84.69 %
2	7.75 %	92.44 %
3	2.65 %	95.09 %
4	1.31 %	96.39 %
5	0.76 %	97.15 %
6	0.39 %	97.54 %
7	0.28 %	97.82 %
...	...	...
17	0.04 %	98.98 %
18	0.03 %	99.01 %
...	...	...

4.5 Incentive Scheme

Warehouse agents gain a low fixed wage plus yearly holiday premium and shift allowance. The weekly working time is specified by the agents' working contracts. No effort-based compensation payment element is in place. Work contracts neither contain requirements for effort nor explicit performance goals. Furthermore, no linkage between earnings and external economic factors (e.g., development of demand or economic growth) is defined.

In contrast to the simple wage model of warehouse agents, managers are provided with effort-based premiums depending on the fulfillment of pre-defined target agreements. Managers are not able to observe the individual output contribution of single warehouse agents and they have no access to the individual performance data. Besides the fact that the managers' offices are outside the warehouse halls, this also results from several other factors, e.g., building floor space, high number of warehouse agents and 24/7 operations. That is, managers only have incomplete information about the working behavior of their employees. For them, this is a disadvantage, because the fulfillment of their individual targets depends to a substantial extend on the performance of their employees. Managers are only able to determine the output of a whole shift group – e.g., on the basis of the fraction of punctual build-ups. Hence, the whole team is held accountable when performance is weak.

Due to the incentive setups and information asymmetry, the build-up process seems to be prone to free riding: Some warehouse agents might work less hard than others because for a worker it seems rational to reduce effort when more productive workers are present. As shown theoretically by Kandel and Lazear (1992) and empirically – among others – by Mas and Moretti (2009), reduced effort by agents imposes negative externalities on their peers. This may result in resentment or sanctions from coworkers. Therefore, it is optimal for a worker to contribute a fair share, and work harder, reducing the productivity gap with his more productive peers (Holmström, 1979, 1982; Kandel and Lazear, 1992; Mas and Moretti, 2009). Whether the authors' findings also apply in the examined environment is one crucial question of this paper.

5 Data

5.1 Data Description and Summary Statistics

We exploit unique field panel data providing information on warehouse agents' historic performances in build-up activities between January 2011 and September 2014 (45 months). Our leading productivity measure is the number of build-up scans per hour. From the full sample of 335 agents, we observe 320 warehouse agents in the estimation sample consolidating pallets over 187 Saturdays. Thus, almost every agent in the warehouse works on Saturdays between 7:00 and 17:00 which brings further support to the claim that shift formation is random. The estimation sample consists of $4,830$ hourly shifts in $2,000$ hours of consolidation (in every hour there can be up to 4 hourly shifts - one for each hall of the warehouse).

Table 5.1 provides basic summary statistics for the dependent and independent variables. On average, an agent scans 10.6 items per hour. At the lower part of the productivity distribution, 10th quantile, average productivity is 2 scans per hour and at the top, 90th quantile, 24 scans per hour. As indicated by the standard deviation in the number of build-up scans (9.3), there is remarkable variation in current productivities across workers. Agents' permanent productivity is estimated in Steinbach (2016) in the fashion of Mas and Moretti (2009) using information on all hourly observations between January 2011 until September 2014 and not only Saturdays and time frame 7:00 am and 5:00 pm. Mean permanent productivity in our sample is very close to zero (about 7.6% of a standard deviation), which additionally verifies that assignment of agents in shifts is unsystematic. By construction, the mean of permanent productivity is zero in the full sample with 335 agents. If managers were strategically and systematically scheduling higher ability agents to Saturdays and peak times, the mean permanent productivity should be well above zero. Agents at the lower quantile have a permanent productivity value of -2.303 while those at the top have a value of 2.927. On average, an agent has completed 413 hours in the consolidation procedure; those at the 10th quantile have completed 34 hours on average while those at the 90th have completed $1,007$ hours.

As agents perform all consolidation of freight on pallets with the help of the forklift, physical condition or age does not matter for productivity. What matters is familiarity with maneuvering the forklift in the halls of the cargo warehouse which we measure with completed hours of consolidation. Similarly to the estimation of permanent productivity, we consider completed hours over all hourly observations between January 2011 until September 2014 and not only those used in the estimation to avoid measurement error. The cargo company employs 10 females who constitute only 3% of the agents. The majority of agents have the same foreign nationality (58%). Native agents comprise the second largest nationality. The omitted category includes other nationalities which amount to 19% of the agents.[17] Each agent is assigned to a manager who is responsible for scheduling the shifts but has no information on individual productivity (cf., Subsection 4.3). The cargo company relies mainly on managers 1 (70%) and 4 (16%) for the consolidation procedure. The composition of an hourly shift may include agents assigned from multiple managers. Agents from the remaining managers – almost 3% – work in other activities of the cargo company, namely truck loading, truck unloading, storing, relocating, consolidating and deconsolidating (break downs). Around 60% of the build-up procedure occurs in hall 1 on the ground floor of the warehouse where the freight is delivered.

In Figure 5.1 we plot productivity by agents' nationality. Both average number of scans and permanent productivity in scans are higher for the foreign agents who comprise the majority, followed by agents with other nationalities and then by native agents. Thus, foreign agents who comprise the majority are the most productive on average. Note that we observe 5 agents in one single hour during Saturdays; later on, we exclude them in estimation.

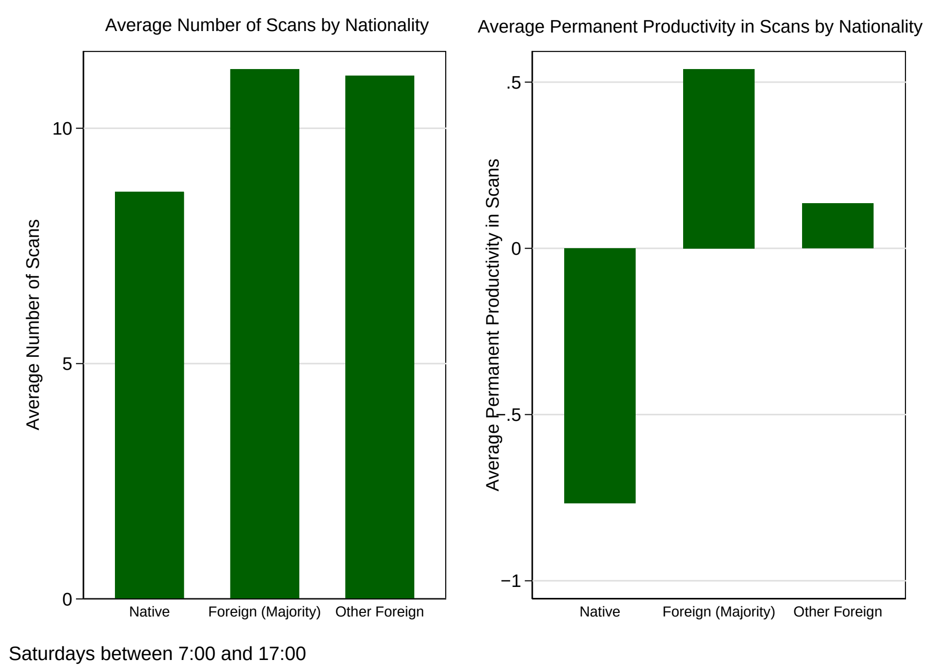
[17] Although we know the nationality of every agent in the sample, we construct a large category "other nationalities" in order to preserve agents' anonymity (certain nationalities correspond to a single agent). Initially, we encounter 21 different nationalities. For the same reason, we do not report minimum and maximum values for continuous variables (correspond to a single agent) or information on all available managers (correspond on two/three agents). We, nevertheless, include information on gender as the cargo company employs 10 females, which satisfies the "rule of 5" (data protection law with respect to reporting results for less than 5 individuals).

Table 5.1: Summary statistics

Continuous variables	Mean	Standard Deviation	10th Quantile	90th Quantile
Number of build-up scans per hour	10.625	9.31	2	24
Permanent productivity in scans	0.160	2.095	-2.303	2.927
Experience in hourly shifts	413.14	424.233	34	1,007
Indicator Variables	Mean	Standard Deviation	Minimum	Maximum
Female	0.029	0.169	0	1
Natives	0.230	0.421	0	1
Foreign nationals (majority)	0.578	0.494	0	1
Other foreign nationals (omitted)	0.192	0.394	0	1
Manager 1	0.669	0.471	0	1
Manager 2	0.062	0.242	0	1
Manager 3	0.077	0.267	0	1
Manager 4	0.164	0.370	0	1
Other managers (omitted)	0.027	0.163	0	1
Hall 1 (Ground Floor)	0.587	0.492	0	1
Hall 2 (Ground Floor)	0.176	0.381	0	1
Hall 3 (First Floor)	0.187	0.390	0	1
Hall 4 (First Floor, omitted)	0.049	0.217	0	1
Number of Observations	30,659			

Notes: Observations for Saturdays between 7:00 and 17:00 for teams with 3 or more agents. Unit of observation for productivity is warehouse agent × one-hour-time interval.

Figure 5.1: Average Number of Scans and Average Permanent Productivity in Scans by Nationality



5.2 Tests for Haphazard Shift Composition

In Sections 4.4-4.3 we describe the institutional context of shift formation in the cargo warehouse and conclude that shift compositions are haphazard. Although possible endogenous group formation does not pose a threat to identification for the outcome equation of peer effects,[18] haphazard shift composition is an important assumption for the estimation of permanent productivity, p_i. Steinbach (2016) estimates p_i a la Mas and Moretti (2009) for the whole sample – and not only Saturdays – as the individual fixed effect from the regression of own productivity on dummies for every possible combination of peer composition, the number of peers and all possible combinations of warehouse hall, day of week and hour of day. In this Section we take a series of steps to further support the claim that shift formation is haphazard.

First, *production with agents from different managers mitigates sorting.* As obvious from Table 5.1, in the cargo warehouse there are multiple managers scheduling the four 8.5-hour work-shifts about four to six weeks in advance. Each manager lacks information not only on individual agent performance but also on the productivity of agents belonging to a different manager. Also, managers schedule work-shifts independently from each other as they belong to different organizations facing different demand so that agents from different managers can end up building up pallets in the same warehouse hall and hour. For our estimation sample, i.e., Saturdays from 07:00 to 17:00, we observe agents from at least two different managers working together in the same hall in around 80% of the hourly shifts (67% for the full sample).

Second, *an agent's average number of hours worked in the build-up procedure does not depend on permanent productivity.* To test whether higher productivity agents work more frequently, we estimate the following model:

$$\bar{s}_i = \alpha + \rho_1 \widehat{p}_i + x_i \delta_1 + u_i,\ i = 1, ..., n \tag{5.1}$$

in which $\bar{s}_i$ denotes the average number of shifts worked defined as the overall number of hours worked in the build-up procedure divided by the number of days the agent was employed in the cargo company, $\widehat{p}_i$ is the estimated permanent productivity for agent i, x_i collects individual characteristics, i.e., gender, nationality, and manager, and u_i is an i.i.d. error term. Due to the high rotation of agents through within-firm relocation, hires and quits in different points in time, we normalize the total number of hours worked with the time the agent has been with the company. Under sorting we expect $\rho_1 > 0$. Table 5.2 presents the estimation results for equation (5.1) for the whole sample and per manager. For managers $1-3$ it is the lower productivity agents who work more frequently on average. None of the estimated coefficients on permanent productivity is statistically significant, which is expected for managers $2-4$ due to the small number of observations. The result is more reliable for manager 1 who regulates the majority of the build-up procedure. Overall, there is no evidence that higher productivity agents work more frequently as it would be

[18] First because the socio-matrix would be exogenous conditional on both individual and time fixed effects, and, second because even if managers tend to strategically assign more productive agents in busier shifts, the time fixed effects transformation would sweep out the manager's selectivity bias as shown by Horrace, Liu, and Patacchini (2016).

the case if managers were designing shift composition strategically.

Table 5.2: Average build-up hours

	(1)	(2)	(3)	(4)	(5)
	All	Manager 1	Manager 2	Manager 3	Manager 4
Permanent productivity	0.000	-0.002	-0.019	-0.023	0.113
	(0.017)	(0.024)	(0.034)	(0.031)	(0.081)
Observations	335	198	52	33	38

Note: Dependent variable is the number of hours worked in the build-up procedure divided by the number of days the agent was employed in the cargo company. Estimation with OLS including a constant term. Specification (1) includes dummies for gender, nationality and manager. Specifications (2)-(5) include dummies for nationality. *, ** and *** denote significance at 10%, 5% and 1% level respectively; bootstrapped standard errors ($1,000$ replications) in parentheses.

Third, *the probability of working during high demand periods does not depend on an agent's permanent productivity*. If shift composition is indeed haphazard then the probability of working during high-demand periods should not depend on an agent's permanent productivity; it should only depend on demand. There are two ways to define high-demand periods: first, Saturdays from 07:00 to 17:00, and second, working in a team on a Saturday from 07:00 to 17:00. For each definition we estimate the probability that an agent works on a Saturday from 07:00 to 17:00 or in a team on a Saturday from 07:00 to 17:00 respectively through models

$$Saturday_{it} = \alpha_i + \eta_1 demand_{it} + \rho_2 \widehat{p}_i + \eta_2 demand_{it} \times \widehat{p}_i + x_i\delta_2 + hall_t\zeta_1 + u_{it} \tag{5.2}$$

$$Team\, Saturday_{it} = \alpha_i + \eta_3 demand_{it} + \rho_3 \widehat{p}_i + \eta_4 demand_{it} \times \widehat{p}_i + x_i\delta_3 + hall_t\zeta_2 + u_{it} \tag{5.3}$$

for $i = 1, ..., n$ and $t = 1, ..., T$, in which the dependent variable takes value 1 if the agent works on a Saturday from 07:00 to 17:00 and 0 otherwise for model (5.2), 1 if the agent works in a team on Saturdays from 07:00 to 17:00 and 0 otherwise for model (5.3), $demand_{it}$ is the average demand in (log) scans during hour t excluding own contribution, $\widehat{p}_i$ is the estimated permanent productivity for agent i, x_i collects individual characteristics as above, $hall_t$ is a set of indicator variables to denote the warehouse hall where production takes place, and u_{it} is an i.i.d. error term. Tables 5.3 and 5.4 present the estimation results for equations (5.2) and (5.3) respectively. Table 5.3 verifies that higher demand and not an agent's permanent productivity increases the probability an agent works on a Saturday from 07:00 to 17:00. It seems that manager 2 assigns higher productivity agents in higher demand Saturdays from 07:00 to 17:00 but the probability increases only slightly compared to demand. Notice that for the same manager if demand is very low then the probability that an agent works on a Saturday from 07:00 to 17:00 decreases in permanent productivity; the effect, though, is not statistically significant. In Table 5.4 only demand for managers 1 and 2 affects the probability of working in a team while the effect is much smaller than in Table 5.3. Overall, from Tables 5.3 and 5.4 there is no evidence that managers 1 and 4 – to whom the majority of observations belongs to – systematically assign higher productivity agents to shifts with higher demand.

Table 5.3: Probability of Working on a Saturday from 07:00 to 17:00

	(1)	(2)	(3)	(4)
	Manager 1	Manager 2	Manager 3	Manager 4
Demand in (log) scans	0.259***	0.250***	0.365***	0.264***
	(0.009)	(0.028)	(0.020)	(0.018)
Permanent productivity	-0.009	-0.035	0.015	-0.017
	(0.007)	(0.021)	(0.010)	(0.028)
Demand in (log) scans ×perm. productivity	0.005	0.025***	-0.009*	-0.000
	(0.003)	(0.009)	(0.005)	(0.014)
Agents	198	52	33	38
Observations	72,854	8,464	6,589	18,116

Note: Dependent variable is the probability of working on a Saturday from 07:00 to 17:00. Estimation results from a Linear Probability Model (LPM) including random effects and dummies for nationality and production hall. *, ** and *** denote significance at 10%, 5% and 1% level respectively; bootstrapped standard errors (1, 000 replications) clustered at the agent level in parentheses.

Table 5.4: Probability of Working in a Team During Saturdays from 07:00 to 17:00

	(1)	(2)	(3)	(4)
	Manager 1	Manager 2	Manager 3	Manager 4
Demand in (log) scans	0.063***	0.096***	0.031	-0.000
	(0.010)	(0.027)	(0.027)	(0.009)
Permanent productivity	0.004	0.034	-0.012	0.006
	(0.012)	(0.028)	(0.022)	(0.023)
Demand in (log) scans ×perm. productivity	-0.004	-0.014	0.006	-0.003
	(0.005)	(0.013)	(0.009)	(0.010)
Agents	192	49	32	35
Observations	22,808	2,241	3,074	5,303

Note: Dependent variable is the probability of working in a team during Saturdays from 07.00 to 17:00. Estimation results from a Linear Probability Model (LPM) including random effects and dummies for nationality and production hall. *, ** and *** denote significance at 10%, 5% and 1% level respectively; bootstrapped standard errors (1, 000 replications) clustered at the agent level in parentheses.

6 Econometric Model, Estimation, and Interpretation

6.1 Econometric Model

A general peer effects model for an agent $i = 1, ..., n$ building pallets in hall $h = 1, 2, 3, 4$ during an hourly interval $t = 1, ..., T$ between 7:00 am and 5:00 pm during Saturday $s = 1, ..., S$ is

$$y_{it} = \lambda \frac{1}{n_{ht}-1} \sum_{j=1, j\neq i}^{n_{ht}} y_{jt} + \gamma \frac{1}{n_{ht}-1} \sum_{j=1, j\neq i}^{n_{ht}} p_{jt} + x_{it}\beta_1 + \frac{1}{n_{ht}-1} \sum_{j=1, j\neq i}^{n_{ht}} x_{jt}\beta_2 + \alpha_i + \theta_s + \varepsilon_{it} \quad (6.1)$$

in which y_{it} denotes the productivity measure, i.e., the natural logarithm of the number of build-up scans in an hour, and $\frac{1}{n_{ht}-1} \sum_{j=1, j\neq i}^{n_{ht}} y_{jt}$ the average peer current productivity in hall h and hour t so that scalar coefficient λ denotes the endogenous social interactions parameter. Notice that the number of peers, $n_{ht}-1$, depends on production location $h=1,2,3,4$ as agents interact only with peers in the same hall during hour t. $\frac{1}{n_{ht}-1}\sum_{j=1,j\neq i}^{n_{ht}} p_{jt}$ is the average peer permanent productivity in hall h and time t; its effect is measured by the scalar coefficient γ. In estimation we use the estimate, $\widehat{p}_i$, from Steinbach (2016). By construction, average peer permanent productivity is zero. $1\times k$ vector x_{it} collects individual characteristics – such as gender or experience – so that $k\times 1$ vector β_1 measures own effects. $\frac{1}{n_{ht}-1}\sum_{j=1,j\neq i}^{n_{ht}} x_{jt}$ denotes peer average characteristics, such as the proportion of female peers or the peer average experience in hall h and time t. The $1\times k$ coefficient vector β_2 measures the effect from peer average characteristics. Average peer permanent productivity and characteristics are *exogenous* social effects, also known as contextual or compositional effects, whereas average peer current productivity is the *endogenous* social effect because it is simultaneously determined with own current productivity at every h and t. The error term, $\boldsymbol{\varepsilon}_{it}$, is independent and identically distributed across i and t with mean zero and variance σ_{ε}^2. The model allows for unobserved individual heterogeneity with the inclusion of scalar α_i. In the model estimated by Mas and Moretti (2009) and Steinbach (2016) α_i is simply p_i, i.e., an agent's permanent productivity. In model (6.1) we simply define unobserved heterogeneity more flexibly so that α_i includes an agent's ability to consolidate pallets as well as an agent's intrinsic motivation, speed of learning or preferences. Model (6.1) captures time effects such as common warehouse shocks and correlated effects, e.g., higher demand on Saturdays before Christmas or Valentine's day, through vector θ_s for day (Saturday) $s=1,...,S$. We treat both individual and time effects as fixed, meaning we allow for α_i and θ_s to be correlated with any of the explanatory variables. We eliminate both agent and day fixed effects by subtracting observations from their means over time and individuals respectively.

We introduce the $n_{ht}\times n_{ht}$ nonstochastic and time-varying socio-matrix capturing influences among the n_{ht} agents in hall $h=1,2,3,4$ and time t

$$\boldsymbol{W}_{n_{ht}} = \frac{1}{n_{ht}-1}(\iota_{n_{ht}}\iota_{n_{ht}}^{\prime} - \boldsymbol{I}_{n_{ht}}) = \begin{pmatrix} 0 & \frac{1}{n_{ht}-1} & \cdots & \frac{1}{n_{ht}-1} \\ \frac{1}{n_{ht}-1} & \ddots & \ddots & \vdots \\ \vdots & \ddots & \ddots & \frac{1}{n_{ht}-1} \\ \frac{1}{n_{ht}-1} & \cdots & \frac{1}{n_{nt}-1} & 0 \end{pmatrix} \tag{6.2}$$

in which $\iota_{n_{ht}}$ denotes the $n_{ht}\times 1$ vector of ones and $I_{n_{ht}}$ the $n_{ht}\times n_{ht}$ identity matrix. Elements on the main diagonal are zero in order to exclude self-influence. Matrix $\boldsymbol{W}_{n_{ht}}$ maps a complete network in each hall $h=1,2,3,4$ and hourly interval t: each agent affects (and is affected by) every peer identically.[19] The general peer effects model for the n_{ht} agents building pallets in hall $h=1,2,3,4$

[19]We do not define a network as in Lindquist, Sauermann, and Zenou (2015), for instance, over a Saturday or an 8-hour shift because we want to avoid using an agent's peers-of-peers' characteristics in hourly shift $t+1$ as an instrument for $\boldsymbol{W}_{n_{ht}t}Y_{n_{ht}t}$ occurring in hourly shift t. To illustrate, during a late shift from 14:00 to 22:00, assume agents A and B build together from 14:00 to 15:00 while agents B and C from 16:00 to 17:00. Defining a network (instead of a complete network) implies that A's productivity during 14:00 to 15:00 is indirectly affected by the exogenous characteristics of B's *future* peer C. Given our context, we define repeated group interactions over time as in Mas and Moretti (2009) and the empirical illustration of Horrace, Liu, and Patacchini (2016).

and hourly interval $t = 1, ..., T$ between 7:00 am and 5:00 pm during Saturday $s = 1, ..., S$ becomes

$$Y_{n_{ht}t} = \lambda \boldsymbol{W}_{n_{ht}t} Y_{n_{ht}t} + \gamma \boldsymbol{W}_{n_{ht}t} P_{n_{ht}t} + \boldsymbol{X}_{n_{ht}t}\beta_1 + \boldsymbol{W}_{n_{ht}t}\boldsymbol{X}_{n_{ht}t}\beta_2 + \alpha_{n_{ht}} + \theta_s \iota_{n_{ht}} + \varepsilon_{n_{ht}t} \tag{6.3}$$

in which $Y_{n_{ht}t}$, $P_{n_{ht}t}$, $\alpha_{n_{ht}}$, $\varepsilon_{n_{ht}t}$ are $n_{ht} \times 1$ vectors, $\boldsymbol{X}_{n_{ht}t}$ is a $n_{ht} \times k$ matrix, λ and γ are scalar parameters while β_1 and β_2 are $k \times 1$ parameter vectors. Accordingly, we introduce the $n_t \times n_t$ socio-matrix for the $n_t = n_{1t} + n_{2t} + n_{3t} + n_{4t}$ agents building pallets during an hourly interval t in all four halls of the cargo warehouse

$$\boldsymbol{W}_{n_t t} = \begin{pmatrix} \boldsymbol{W}_{1t} & \boldsymbol{0} & \cdots & \boldsymbol{0} \\ \boldsymbol{0} & \boldsymbol{W}_{2t} & \boldsymbol{0} & \vdots \\ \vdots & \boldsymbol{0} & \boldsymbol{W}_{3t} & \boldsymbol{0} \\ \boldsymbol{0} & \cdots & \boldsymbol{0} & \boldsymbol{W}_{4t} \end{pmatrix}. \tag{6.4}$$

Socio-matrix (6.4) is block-diagonal, row-normalized since each block is row-normalized, and maps a noncomplete network as agents from different halls do not affect each other. The general peer effects model for the n_t agents building pallets in hourly interval $t = 1, ..., T$ between 7:00 am and 5:00 pm during Saturday $s = 1, ..., S$ is

$$Y_{n_t t} = \lambda \boldsymbol{W}_{n_t t} Y_{n_t t} + \gamma \boldsymbol{W}_{n_t t} P_{n_t t} + \boldsymbol{X}_{n_t t}\beta_1 + \boldsymbol{W}_{n_t t}\boldsymbol{X}_{n_t t}\beta_2 + \alpha_{n_t} + \theta_s \iota_{n_t} + \varepsilon_{n_t t}. \tag{6.5}$$

To exemplify identification and sources of variation we write the same equation for Saturday $s = 1, ..., S$

$$Y_{n_s s} = \lambda \boldsymbol{W}_{n_s s} Y_{n_s s} + \gamma \boldsymbol{W}_{n_s s} P_{n_s s} + \boldsymbol{X}_{n_s s}\beta_1 + \boldsymbol{W}_{n_s s}\boldsymbol{X}_{n_s s}\beta_2 + \alpha_{n_s} + \theta_s \iota_{n_s} + \varepsilon_{n_s s} \tag{6.6}$$

in which $\boldsymbol{W}_{n_s s}$ is a block diagonal matrix with blocks comprised of (6.4) for each t between 7:00 am and 5:00 pm.

6.2 Estimation

Notice that peer average current productivity, $\boldsymbol{W}_{n_s s} Y_{n_s s}$, is endogenous by construction of the model. Suppressing fixed effects yields

$$E(\boldsymbol{W}_{n_s s} Y_{n_s s} \varepsilon'_{n_s s}) = \sigma^2_\varepsilon \boldsymbol{W}_{n_s s}(I_{n_s} - \lambda \boldsymbol{W}_{n_s s})^{-1} \neq 0. \tag{6.7}$$

There exist two possible solutions: first, find instruments for $\boldsymbol{W}_{n_s s} Y_{n_s s}$ and estimate the model with 2SLS or GMM (see Kelejian and Prucha 1998, 1999, 2002; Lee 2002, 2003, 2007; Bramoullé, Djebbari, and Fortin 2009; Lee, Liu, Patacchini, and Zenou 2012; Lee and Yu 2014) and, second, estimate the reduced form with ML (see Lee, 2004, 2007; Yu, de Jong, and fei Lee, 2008; Davezies, D'Haultfoeuille, and Fougére, 2009; Lee and Yu, 2010; Lee, Liu, and Lin, 2010; Lee and Yu, 2012;

Horrace, Liu, and Patacchini, 2016). In this chapter, we proceed with the former and in order to gain insight into identification we derive the reduced form for equation (6.5), i.e., an equivalent equation in which all of the right-hand-side variables are exogenous

$$Y_{n_s s} = (I_{n_s} - \lambda \boldsymbol{W}_{n_s s})^{-1} (\gamma \boldsymbol{W}_{n_s s} P_{n_s s} + \boldsymbol{X}_{n_s s}\beta_1 + \boldsymbol{W}_{n_s s}\boldsymbol{X}_{n_s s}\beta_2 + v_{n_s s}) \tag{6.8}$$

in which $v_{n_s s}$ is the error term including both agent and time fixed effects as well as an *i.i.d.* term. From the reduced form we get

$$E(\boldsymbol{W}_{n_s s} Y_{n_s s}) = \boldsymbol{W}_{n_s s}(I_{n_s} - \lambda \boldsymbol{W}_{n_s s})^{-1} (\boldsymbol{X}_{n_s s}\beta_1 + \boldsymbol{W}_{n_s s}\boldsymbol{X}_{n_s s}\beta_2) \tag{6.9}$$

assuming without loss of generality that individual and time effects have zero mean. Also, notice that $E(\boldsymbol{W}_{n_s s} P_{n_s s}) = 0$ since the socio-matrix is nonstochastic and by construction average peer permanent productivity has a zero mean. Due to the row-normalization of the socio-matrix, we can assume $\lambda \in (-1, 1)$ so that we can rewrite the reduced form as

$$E(\boldsymbol{W}_{n_s s} Y_{n_s s}) = \boldsymbol{W}_{n_s s}\left(I_{n_s} + \lambda \boldsymbol{W}_{n_s s} + \lambda^2 \boldsymbol{W}^2_{n_s s} + \lambda^3 \boldsymbol{W}^3_{n_s s} + \lambda^4 \boldsymbol{W}^4_{n_s s} + \cdots\right) \times \\ (\boldsymbol{X}_{n_s s}\beta_1 + \boldsymbol{W}_{n_s s}\boldsymbol{X}_{n_s s}\beta_2). \tag{6.10}$$

Equation (6.10) shows that the best instrumental variable for $\boldsymbol{W}_{n_s s} Y_{n_s s}$ is simply an estimate of the right-hand side meaning $\boldsymbol{W}_{n_s s} Y_{n_s s}$ can be approximated with a power series expansion of the exogenous variables. Then, instrumental variables for $\boldsymbol{W}_{n_s s} Y_{n_s s}$ are the linearly independent columns of $\boldsymbol{W}^2_{n_s s} Y_{n_s s}$ (or the within-transformed equivalent – see, for instance, Bramoullé, Djebbari, and Fortin, 2009). $\boldsymbol{W}_{n_s s}\boldsymbol{X}_{n_s s}$ denotes peer average exogenous characteristics and $\boldsymbol{W}^2_{n_s s}\boldsymbol{X}_{n_s s}$ peer average exogenous characteristics of the peers. Since a peer's peer does not exist for less than 3 agents, identification requires teams with at least 3 agents present in a warehouse hall.

Since interactions occur in groups one issue is that the focal agent's peers of peers are also the focal agent's peers. During an hourly shift t at a hall h there are two sources of influence towards the focal agent: a *direct* influence from the focal agent's peers and an *indirect* influence that reaches the focal agent only through peers of the peers. To illustrate how direct and indirect influences make sense, visualize the agents building pallets in the cargo warehouse halls with the help of the forklift as depicted in Figures 4.1 and 4.4, respectively. Assume that 3 agents – the focal and two peers – are building pallets in hall 1 from 9:00 am to 10:00 am. The agents maneuver their forklifts so that they face each other when they place freight on the pallets but have their backs turned whenever they load freight on the forklift from the designated areas of the hall. Loading freight on the forklift and placing the freight on the pallet can take from several seconds to a few minutes. During that hour, the focal agent's output is influenced directly by peer output, that is whenever agents can see each other. Whenever the focal agent turns to load cargo on the forklift from the sides of the warehouse, the other two agents continue to see and, therefore, influence each other.

Consecutively, imagine now that the second peer turns to load freight and loses sight of the focal agent and the first peer. The focal agent returns to the pallet and is now influenced *directly* by the first peer (because they face each other) and *indirectly* by the second peer through the first (because of their interaction a few moments ago). Therefore, the build-up procedure entails a chain of indirect influences among agents that we can exploit to construct valid instruments in the form of peers' peer characteristics.[20]

The production setting excludes endogenous group formation because first, agents cannot select shifts and, second, managers have incomplete information about agents' performances and cannot schedule the same agents to work every Saturday (see Section 4.4). Therefore, the socio-matrix specifying average effects is exogenous and nonstochastic and so are the excluded instrumental variables of the form $\boldsymbol{W}^2_{n_s s}\boldsymbol{X}_{n_s s}$. Identification of equation (6.5) relies on two sources of variation: *team size* variation and variation in *team composition* so that $\boldsymbol{W}^2_{n_s s}\boldsymbol{X}_{n_s s}$ is not a linear combination of $\boldsymbol{W}_{n_s s}\boldsymbol{X}_{n_s s}$. Team size variation refers to the different number of agents working in each hall during an hourly interval t or during the whole Saturday s. Variation in team composition emerges when the focal agent works for at least 2 hourly intervals during a Saturday s and is exposed to a different peer group in every hourly interval, which is plausible according to our analysis in Section 4.4. Lee (2007); Davezies, D'Haultfoeuille, and Fougére (2009); Bramoullé, Djebbari, and Fortin (2009) demonstrate how group size variation identifies structural parameters when interactions occur in groups and the model includes group fixed effects. Boucher, Bramoullé, Djebbari, and Fortin (2014) emphasize that high dispersion in group sizes is crucial for identification. In our case groups vary from 3 to 20 agents (18 distinct group sizes) for the whole sample while only from 3 to 9 in smaller groups (7 distinct group sizes) and 10 to 20 for larger groups (11 distinct group sizes). We exploit information from the hours and the day when export demand peaks at the cargo company, namely 7:00 am to 5:00 pm on Saturdays, when all group sizes are observed and agents work in different team compositions every hour. Thereby we exploit both sources of variation to identify parameters under the same demand conditions. We estimate the model with 2SLS, we bootstrap standard errors when the model includes peer permanent productivity while we take into account possible correlation among individual observations.

6.3 Interpretation and Behavioral Mechanisms

Parameters λ and γ are the parameters of interest. While both describe peer productivity measures (see Section 3), they differ as an agent's productivity during a specific hourly interval (current productivity) might deviate from her productivity type (permanent high or low type). For instance, although we may introduce high permanent productivity agents in an hourly shift in order to increase a team's average permanent productivity, it does not necessarily mean that we increase

[20]Notice that the peers' of peers characteristics in period $t-1$ could also serve as excluded instruments for period t. If the focal agent was active in period $t-1$ as well, then the peers' peers were also peers of the focal agent. We leave the latter as well as estimation with QML for future research. A potential problem with QML is that the model can not always be written in an autoregressive form in the presence of individual and time fixed effects; therefore, the likelihood function cannot be derived.

average current productivity because newly-introduced agents might underperform that specific hour. Furthermore, although peer permanent productivity effects make sense only when agents know or have formed an expectation about their peers' type of productivity, peer current effects are meaningful even if all agents work together for the first time. In our setting, agents operate in five other different activities apart from building up pallets, i.e., truck loading, truck unloading, storing, relocating, and breaking down pallets, all with the use of a forklift and barcode scanner. Therefore, there is little doubt about whether a coworker's high or low productivity signal is known. Even if two agents meet for the first time in the consolidation process, one hour is more than enough to place each other on the permanent productivity distribution. Econometrically, the implication is that peer permanent productivity effects can be estimated only when panel data are available while peer current productivity effects can be estimated with a cross-section of data. Also notice that peer permanent productivity is a contextual effect, i.e., an exogenous social effect, whereas peer contemporary productivity is endogenous by construction of the model: under conditions (i.e., interactions driven by learning and not conformity), only peer current/contemporary productivity effects have the potential to generate a social multiplier effect.

Parameter λ captures the contemporaneous behavioral effect in hourly productivity outcomes. In order to isolate the effect of peer contemporary productivity from the effect of peer permanent productivity, we must introduce an agent in the shift whose permanent productivity is the same as the average permanent productivity in the shift. Thereby, we induce a change in the average peer contemporary productivity while keeping the average peer permanent productivity constant. Due to the row-normalization of the socio-matrix we assume $\lambda \in (-1, 1)$. If $0 < \lambda < 1$ then an agent increases own performance when the average of the team increases performance currently, i.e., agents behave similarly. The behavioral mechanism behind $0 < \lambda < 1$ is conformity, i.e., agents adapt to the higher average current performance of the peer group because deviations are costly in terms of utility. Conformity refers to an individual's aversion of standing out or differentiating behavior from the average. Boucher and Fortin (2016) show that $0 < \lambda < 1$ may actually imply conformity, complementarity or both. Complementarity occurs when agents observe and learn from faster peers and, therefore, generates a social multiplier effect; interventions to increase productivity are amplified at the aggregate level. On the other hand, the social multiplier effect is absent in the case of conformity, hence the analysis merits from discovering which specific agents to target in order to increase team productivity.[21] If $\lambda = 0$, then an agent's performance does not depend on peer current average performance during an hourly shift. Finally, if $-1 < \lambda < 0$, an agent decreases own performance when the average of the team increases performance, i.e., agents behave dissimilarly. Such negative effects are not common in the social interactions literature; Sommer (2016) is the first to explore the connection between microeconomic and statistical models that produce $-1 < \lambda < 0$ as anticonformist behavior.

Parameter γ captures the direction and magnitude of the team composition in terms of high or low ability in building up pallets when an agent with the average contemporary productivity joins

[21] For instance, the key player in a network (Ballester, Calvó-Armengol, and Zenou, 2006; Lindquist, Sauermann, and Zenou, 2015; Zenou, 2016).

the shift. In order to measure the effect of a change in average peer permanent productivity net of changes in average peer contemporary productivity, we must introduce an agent who works at the average current speed so that the change in peer current productivity is zero. As introduced by Mas and Moretti (2009), if $\gamma > 0$, then an increase in average peer permanent productivity results in an increase in own performance due to peer pressure or shame. If $\gamma = 0$, then agents do not adapt their behavior at the task with changes in the average ability of their peers. Finally, if $\gamma < 0$, then agents free-ride meaning they reduce own performance when the average team ability increases as they think their more able peers can finish their task.

In reality, some agents generate spillovers and some conform, some remain unaffected by peers while others behave differently from their peers or free-ride. With a large enough number of observations per agent it is possible to identify individual specific effects (see Mas and Moretti, 2009, for individual heterogeneity in peer permanent productivity, and Aquaro, Bailey, and Pesaran, 2015 who estimate individual heterogeneity in endogenous effects in a spatial model). Although, first, our panel is highly unbalanced with both too few and too many observations per agent so that estimation of individual specific effects is excluded for agents with too few observations, and, second, the German "rule of five" does not allow us to estimate effects for less than five agents (let alone single cases), we – nevertheless – can estimate effects for interesting groups of agents. Furthermore, the inclusion of agent fixed effects renders the socio-matrix robust to possible dependence on individual preferences. For instance, if agents tend to be influenced more by coworkers with whom they are friends or vice versa, this should not play a role for the fixed effects estimation as it conditions on unobserved agent preferences.

7 Estimation Results

Tables 7.1, 7.2 and 7.3 present estimation results for seven plausible social interactions models, first, for the full sample, second, for the sample corresponding to teams of 3 to 9 agents, and, third, for the sample with teams larger than 9 agents. The first column of each of the three tables provides estimation results only with contextual effects excluding peer permanent productivity. In the social interactions literature this model is known as the "reduced form" as it allows for discerning the presence of social interactions effects but not their exact nature meaning behavioral or composition effects. Therefore, the estimated coefficients under column (1) are functions of the structural parameters in baseline equations of Section 6.1. Referring to Table 7.1, none of the peer variables is either economically or statistically significant which signifies lack of social effects. There is evidence of a non-linear effect in own experience in hourly shifts as the estimated coefficients of experience and its square indicate an inverted U-relationship: own experience in hourly shifts increases initially own productivity but after reaching the turning point it starts decreasing productivity. Also, we estimate a differential in the warehouse location: changing production location from hall 4 to hall 1 results in a 18% decrease in own productivity. The magnitude of this effect is huge and casts doubts on the usual practice in the cargo company: hall 1 is always preferred for the consolidation process because it is located closely to the export truck ramps where the freight is unloaded. Only after hall 1 starts filling up with agents driving their forklifts does the cargo company use the remaining halls, first hall 2 which is adjacent to hall 1 and also on the ground floor and then on halls 3 and 4 located on the first floor of the cargo warehouse (see Figure 4.1). The practice results in a spatially congested hall 1, therefore the differential with hall 4 and the lack of an effect between halls 2 and 3 with hall 4. In column (1) of Table 7.2 the square of peer experience is statistically significant which indicates the presence of some social effects. Peer experience and its square have positive and negative signs respectively so that working among more experienced peers increases own productivity up to a maximum point after which it decreases own productivity. A plausible explanation is becoming faster initially by working in a shift with more experienced agents due to imitating and learning but then slower perhaps because of free-riding when peers are highly experienced. With reference to column (1) of Table 7.3, there is an inverted U-shaped relationship between experience in hourly shifts and productivity in scans. Peer experience and its square are highly statistically significant and their signs reveal a U-shaped relationship between experience and productivity: there is a minimum average peer productivity level - about $1,149$ hours - after which own productivity starts increasing. The turning point is almost three times the average hourly shift experience in the sample (see Table 5.1). When production occurs in large groups, peers need more than the average experience in order to see positive effects on own productivity. Finally, notice that consolidating in hall 1 is no longer less productive than in hall 3 (teams larger than 9 agents are not observed in hall 4).

Column (2) of Tables 7.1, 7.2 and 7.3 gather estimation results for the model used by Mas and Moretti (2009). Peer permanent productivity refers to contextual or compositional effects. As column (2) of Table 7.1 reveals and unlike Mas and Moretti (2009) and Steinbach (2016), there are no peer permanent productivity effects as the estimated coefficient is -0.009. This result is in line with the baseline results from Steinbach (2016). As with column (1), own experience has a positive effect and working in hall 1 instead of 4 has a negative effect on own performance. For small team sizes – Table 7.2 and column (2) – the only effect on own performance is that of warehouse production location. The effect of peer permanent productivity does not change once we introduce the whole set of contextual variables - column (3) of Tables 7.1 and 7.2. What is interesting is the results for large team sizes in column (2) of Table 7.3: A 10% increase in peer average permanent productivity decreases own productivity by 0.64% signifying free-riding.[22] As in column (1), own experience in hourly shifts has a non-linear effect on own performance. The effect of free-riding is 0.6% when we include contextual effects as shown in column (3) and the non-linear effects of both own and peer experience linger with the same direction as in column (1). So far, we cannot establish the positive effect of peer permanent productivity on scans productivity found by Mas and Moretti (2009). Instead, we uncover free-riding when agents consolidate pallets in large teams as in Steinbach (2016).

Another strand of the literature such as Horrace, Liu, and Patacchini (2016) and Lindquist,

[22] Steinbach (2016) makes an educated guess about free-riding tendencies as well: The estimation magnitudes on a general level are similar to the magnitudes herein, however, lacking statistical significance in most cases.

Sauermann, and Zenou (2015) focus on the estimation of peer current productivity effects alone. Therefore, in columns (4) and (5) of Tables 7.1, 7.2, and 7.3 we present estimation results, first, only with endogenous social effects and then with both endogenous and exogenous social effects. For the full sample and the sample of small groups the estimate of peer current productivity is practically zero (notice that the parameter space is $(-1, 1)$ due to the row-normalization of the socio-matrix). The only factor that matters in both samples is the production location and, more specifically, production in hall 1.[23] When agents undertake consolidation in large groups, there is a positive effect from peer current productivity. The magnitude is larger and more significant when we include contextual effects in the equation – see column (5). Furthermore, there is evidence of non-linear relationships between own and peer experience with own productivity.

Mas and Moretti (2009) in estimating peer permanent productivity parameters admit that *"a possible interpretation of our estimates is that they capture some combination of a true effect of permanent productivity and a true effect of contemporary coworker effort/productivity"*. In reality both effects could be at play and this is exactly what we aim at: Identify if peer productivity effects are of contemporary or permanent nature. In each of the models in columns (4) and (5) we add peer permanent productivity as an additional contextual effect. For the full sample in Table 7.1 and columns (6) and (7) we fail to establish the presence of peer productivity effects. Again, own experience affects own productivity in the same direction as in previous specifications. In small teams there is only some weak evidence of a non-linear relationship in peer experience. The warehouse location indicators capture correlated effects: consolidation in hall 1 is always less productive for the full sample and the small teams.

As we move to large team sizes, we uncover both peer current and permanent productivity effects of opposite direction. Regardless of the presence of exogenous social effects, faster contemporary consolidation of pallets affects own performance positively while a higher ability shift composition affects own performance negatively. Additionally, what matters for own productivity is own experience through a concave function. Remember that experience in shifts captures familiarity with operating the forklift (see Figure 4.4). The maximum is $1,297$ hours and highly statistically significant which indicates experience has a positive effect on performance until the agent completes $1,297$ hours; after this point every additional hour has a negative effect on own productivity. The negative effect of experience is relevant for only 14 agents in the sample who have actually completed more than $1,297$ hours of consolidation with the forklift. The estimated parameter for the endogenous social effects in the generalized model of column (7) is 0.65 which is quite large given the assumption that the parameter space for the endogenous effects is $(-1, 1)$. Agents build pallets faster when the average of their peers increases speed and slower when the average of their peers decreases speed.[24] The model of column (7) also captures indirect cross-sectional dependencies through contextual effects, i.e., the composition of the shift in terms of ability and other exogenous

[23] These results are robust with hourly instead of day fixed effects. Initially we split the small teams sample into two subsamples: 3 to 5 and 6 to 9. Results are similar so we merged the two samples in one.

[24] The behavioral mechanism behind may be attributed to conformism or complementarities - we can not discern between the two for the moment. Steinbach and Tatsi (2016) tackle this issue in future research.

agent characteristics. The only contextual factor that matters is peer ability: a 10% increase in peer average permanent productivity decreases own productivity by 0.78%.

How do peer current and permanent productivity estimates compare?

The estimated coefficient for peer permanent productivity is the marginal effect when peer current productivity, composition of the shift and the production location are fixed. Although the absolute value of the magnitude is much smaller than that of peer current productivity, it indicates alarming performance reductions. Similarly, we can perceive the endogenous effects estimate as a marginal effect with the composition of the shift and the location fixed. A change in peer current productivity, though, induces a change in peer permanent productivity unless it originates from newly-hired agents in the warehouse. The rationale is that permanent productivity is a signal of low or high ability in consolidating pallets and that an agent needs to work with other agents at least once before forming a perception of their true permanent ability. Working with new agents implies no prior knowledge of their permanent productivity. Therefore, a 10% increase in peer current productivity induced by the introduction of newcomers in the shift increases own productivity by 6.5% which is multiple times larger, in terms of absolute value, than the free-riding effect. Overall, the contemporaneous peer behavior with respect to productivity is more important than the permanent peer signal – both economically and statistically.

Why do agents behave differently when working in smaller and larger teams?

The answer lies in the *"sense of monitoring"* and *"spatial proximity*". Agents in smaller groups behave independently because they fail to feel monitored or perceive the presence of others who are too far away. Remember that each hall spans over a $4,000$ square meter area. Hence, in smaller teams, agents do not adapt their current productivity to the productivity of their peers and do not respond to the ability composition of the shift. Agents in larger groups behave dependently because of *spatial proximity*: They are more likely to work closer to each other in a hall. However, it is hard to monitor the other 9 agents in the shift and even harder to monitor the other 19 agents. When agents perceive an increase in the average peer ability in the hourly shift, they decrease own speed. One explanation is that they perceive it as an opportunity to free-ride because they think it is unlikely to get caught when the hall is full, i.e., they feel comfortable enough to slow down (e.g., agents might think others can do the job, see it as a good time to visit the toilette, go out and smoke, or chat with each other).

As a last comment, notice that *"sense of monitoring"* and *"spatial proximity*" can be deemed as exogenous because agents follow strict process rules for each activity. According to working instructions, the build-up freight has to be placed near to the designated storage locations (which are close to the build-up locations in the middle of the hall) - before the build-up starts. Therefore, there is limited space for the focal agent to choose where to build the pallet. Thus, the possibility to completely hide from others to avoid being monitored is ruled out. Furthermore, even if each warehouse hall spans over $4,000\text{m}^2$, freight is placed around the hall and the middle is free for pallet

Table 7.1: Peer Effects Models – All Team Sizes

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Peer current productivity	-	-	-	-0.065	-0.020	-0.024	0.101
				(0.207)	(0.226)	(0.283)	(0.278)
Peer permanent productivity	-	-0.009	-0.010*	-	-	-0.007	-0.016
		(0.006)	(0.006)			(0.023)	(0.019)
Own experience $\times 1000$	0.082***	0.083**	0.082**	0.083***	0.082***	0.083**	0.083**
	(0.030)	(0.034)	(0.034)	(0.030)	(0.030)	(0.035)	(0.035)
Own experience squared	-0.000*	-0.000	-0.000	-0.000*	-0.000*	-0.000	-0.000
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Peer experience $\times 1000$	0.022	-	0.046	-	0.028	-	0.034
	(0.063)		(0.062)		(0.087)		(0.069)
Peer experience squared	-0.000	-	-0.000*	-	-0.000	-	-0.000
	(0.000)		(0.000)		(0.000)		(0.000)
Female peers	0.057	-	0.044	-	0.054	-	0.053
	(0.064)		(0.064)		(0.077)		(0.067)
Native peers	0.035	-	0.028	-	0.032	-	0.041
	(0.040)		(0.041)		(0.057)		(0.056)
Foreign peers (majority)	0.018	-	0.025	-	0.019	-	0.024
	(0.036)		(0.037)		(0.038)		(0.037)
Manager 1 peers	-0.076	-	-0.074	-	-0.076	-	-0.077
	(0.078)		(0.080)		(0.078)		(0.080)
Manager 2 peers	-0.037	-	-0.037	-	-0.036	-	-0.039
	(0.084)		(0.084)		(0.083)		(0.084)
Manager 3 peers	-0.020	-	0.000	-	-0.014	-	-0.015
	(0.087)		(0.087)		(0.099)		(0.093)
Manager 4 peers	0.004	-	0.009	-	0.007	-	-0.004
	(0.079)		(0.080)		(0.083)		(0.085)
Hall 1	-0.199***	-0.214***	-0.209***	-0.223***	-0.205***	-0.219***	-0.187***
	(0.035)	(0.037)	(0.037)	(0.066)	(0.071)	(0.065)	(0.068)
Hall 2	0.001	-0.017	-0.006	-0.013	0.000	-0.016	-0.007
	(0.032)	(0.032)	(0.033)	(0.031)	(0.033)	(0.034)	(0.034)
Hall 3	-0.004	-0.005	-0.002	-0.007	-0.004	-0.005	-0.000
	(0.029)	(0.030)	(0.030)	(0.029)	(0.029)	(0.031)	(0.032)

Note: Dependent variable is (log) number of build-up scans in 1 hour. 30,654 observations for 315 agents and 187 Saturdays. All specifications include agent fixed effects, time fixed effects as well as indicator variables for team size (4 to 20 agents). *, ** and *** denote significance at 10%, 5% and 1% level respectively. Specifications under columns (1)-(3) are estimated with OLS; agent-clustered standard errors in parentheses in column (1); bootstrapped standard errors (1000 replications) in parentheses clustered at the agent level in columns (2) and (3). Specifications under columns (4)-(7) are estimated with 2SLS; agent-clustered standard errors in parentheses in columns (4) and (5); bootstrapped standard errors (1000 replications) clustered at the agent level in columns (6) and (7). Excluded instruments are second order social effects of exogenous variables. Specifications pass tests for underidentification (reject null of underidentification at any level of significance), overidentification (largest test statistic is 1.308 with p-value 0.253 and smallest is 0.806 with p-value 0.668) and weak instruments (smallest test statistic is 17.802 and largest is 28.311).

Table 7.2: Peer Effects Models – Production with 3 to 9 Agents

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Peer current productivity	-	-	-	-0.047	0.031	-0.271	-0.117
				(0.232)	(0.263)	(0.470)	(0.491)
Peer permanent productivity	-	-0.002	-0.003	-	-	0.020	0.005
		(0.007)	(0.007)			(0.039)	(0.033)
Own experience ×1000	0.031	0.031	0.031	0.032	0.030	0.034	0.032
	(0.044)	(0.049)	(0.049)	(0.043)	(0.044)	(0.050)	(0.050)
Own experience squared	-0.000*	-0.000	-0.000	-0.000	-0.000	-0.000	-0.000
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Peer experience	0.124*	-	0.131*	-	0.114	-	0.151
	(0.073)		(0.073)		(0.111)		(0.114)
Peer experience squared	-0.000***	-	-0.000***	-	-0.000*	-	-0.000**
	(0.000)		(0.000)		(0.000)		(0.000)
Female peers	0.076	-	0.072	-	0.080	-	0.066
	(0.071)		(0.072)		(0.083)		(0.084)
Native peers	0.012	-	0.011	-	0.018	-	-0.006
	(0.043)		(0.044)		(0.061)		(0.077)
Foreign peers (majority)	0.007	-	0.009	-	0.005	-	0.009
	(0.037)		(0.037)		(0.041)		(0.038)
Manager 1 peers	-0.083	-	-0.082	-	-0.084	-	-0.078
	(0.079)		(0.079)		(0.079)		(0.082)
Manager 2 peers	-0.057	-	-0.057	-	-0.059	-	-0.051
	(0.085)		(0.085)		(0.086)		(0.090)
Manager 3 peers	-0.043	-	-0.037	-	-0.052	-	-0.020
	(0.085)		(0.086)		(0.108)		(0.112)
Manager 4 peers	-0.027	-	-0.025	-	-0.032	-	-0.011
	(0.082)		(0.083)		(0.090)		(0.101)
Hall 1	-0.182***	-0.197***	-0.185***	-0.206***	-0.175**	-0.237***	-0.204**
	(0.036)	(0.038)	(0.038)	(0.069)	(0.072)	(0.079)	(0.087)
Hall 2	0.004	-0.014	0.002	-0.013	0.004	-0.003	0.005
	(0.033)	(0.033)	(0.034)	(0.032)	(0.034)	(0.039)	(0.038)
Hall 3	-0.005	-0.008	-0.005	-0.009	-0.005	-0.012	-0.007
	(0.030)	(0.029)	(0.029)	(0.030)	(0.030)	(0.031)	(0.032)

Note: Dependent variable is (log) number of build-up scans in 1 hour. 19,431 observations for 303 agents and 187 Saturdays. All specifications include agent and time fixed effects. *, ** and *** denote significance at 10%, 5% and 1% level respectively. Specifications under columns (1)-(3) are estimated with OLS; agent-clustered standard errors in parentheses in column (1); bootstrapped standard errors (1000 replications) in parentheses clustered at the agent level in columns (2) and (3). Specifications under columns (4)-(7) are estimated with 2SLS; agent-clustered standard errors in parentheses in columns (4) and (5); bootstrapped standard errors (1000 replications) clustered at the agent level in columns (6) and (7). Excluded instruments are second order social effects of exogenous variables. Specifications pass tests for underidentification (reject null of underidentification at any level of significance), overidentification (largest test statistic is 2.409 with p-value 0.12 and smallest is 1.042 with p-value 0.307) and weak instruments (smallest test statistic is 20.156 and largest is 24.444).

Table 7.3: Peer Effects Models – Production with 10 to 20 Agents

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Peer current productivity	-	-	-	0.443*	0.604**	0.609**	0.655**
				(0.237)	(0.290)	(0.258)	(0.297)
Peer permanent productivity	-	-0.064***	-0.060***	-	-	-0.090***	-0.078***
		(0.017)	(0.020)			(0.022)	(0.022)
Own experience ×1000	0.132***	0.138**	0.133**	0.163***	0.161***	0.169***	0.165***
	(0.050)	(0.056)	(0.057)	(0.053)	(0.054)	(0.060)	(0.060)
Own experience squared	-0.000**	-0.000**	-0.000*	-0.000***	-0.000***	-0.000**	-0.000**
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Peer experience ×1000	-0.575***	-	-0.447***	-	-0.441**	-	-0.266
	(0.162)		(0.163)		(0.176)		(0.186)
Peer experience squared	0.000***	-	0.000**	-	0.000*	-	0.000
	(0.000)		(0.000)		(0.000)		(0.000)
Female peers	-0.069	-	-0.143	-	0.152	-	0.075
	(0.205)		(0.207)		(0.219)		(0.219)
Native peers	-0.022	-	-0.100	-	0.201	-	0.119
	(0.105)		(0.108)		(0.151)		(0.146)
Foreign peers (majority)	-0.008	-	-0.007	-	0.026	-	0.031
	(0.095)		(0.093)		(0.099)		(0.098)
Manager 1 peers	-0.105	-	0.012	-	-0.249	-	-0.110
	(0.213)		(0.221)		(0.216)		(0.226)
Manager 2 peers	-0.074	-	0.005	-	-0.094	-	0.007
	(0.258)		(0.264)		(0.261)		(0.271)
Manager 3 peers	-0.188	-	0.029	-	-0.305	-	-0.035
	(0.282)		(0.289)		(0.280)		(0.292)
Manager 4 peers	0.134	-	0.216	-	-0.150	-	-0.067
	(0.232)		(0.235)		(0.247)		(0.252)
Hall 1	0.162	0.012	0.008	0.267	0.256	-0.031	0.065
	(0.246)	(0.235)	(0.267)	(0.225)	(0.260)	(0.252)	(0.281)
Hall 2	0.396	0.245	0.243	0.370	0.332	0.037	0.129
	(0.250)	(0.238)	(0.272)	(0.235)	(0.266)	(0.274)	(0.295)

Note: Dependent variable is (log) number of build-up scans in 1 hour. $11,116$ observations for 273 agents and 177 Saturdays. All specifications include agent and time fixed effects. *, ** and *** denote significance at 10%, 5% and 1% level respectively. Specifications under columns (1)-(3) are estimated with OLS; agent-clustered standard errors in parentheses in column (1); bootstrapped standard errors (1000 replications) in parentheses clustered at the agent level in columns (2) and (3). Specifications under columns (4)-(7) are estimated with 2SLS; agent-clustered standard errors in parentheses in columns (4) and (5); bootstrapped standard errors (1000 replications) clustered at the agent level in columns (6) and (7). Excluded instruments are second order social effects of exogenous variables. Specifications pass tests for underidentification (reject null of underidentification for at level of significance), overidentification (largest test statistic is 1.747 with p-value 0.417 and smallest is 0.068 with p-value 0.966) and weak instruments (smallest test statistic is 30.723 and largest is 79.534).

consolidation. This means that agents build pallets usually in lines. For the case of many parallel build-ups, agents align neighbored pallets alternately in the pattern of a “W-shape” or a spaced “double line” to reduce the possibility of congestion. Hence, even if 20 agents are active, those furthest away from each other can at least see the height of a pallet being built rising.

7.1 Who is the Free-rider?

So far, not only do we know that agents respond to peer performance in large teams but also their response depends on current or permanent performance measures. Although in large teams agents become more productive when the average peer current productivity increases through newcomers in the shift, they tend to decrease own productivity when they perceive an increase in the peer average permanent productivity. The latter should alarm the company management even if the positive effects from working among faster newcomers surpass the negative effects of working with high ability peers because it points to inefficient use of human resources. Agents seem to willingly free-ride because they know or speculate that their higher ability peers will finish their work.

In team production processes, free-riding among workers is likely to be an issue if individual inputs cannot be perfectly observed by participants and principals and inadequate structures regarding incentives and monitoring are in place. Cheating agents cannot be identified if the output of the whole team is the only observable indicator of individual effort (Holmström, 1979, 1982). Our results reveal that in large teams, familiarity with coworkers' ability may induce free-riding behaviors.

In this Section we try to figure out whether the negative effect of peer permanent productivity is nonlinear or heterogeneous with respect to observable agents' characteristics. Tables 7.4-7.7 present results of augmented peer effects models for production undertaken by teams of 10 to 20 agents. In Table 7.4, there is very weak evidence that peer permanent productivity varies with own or peer experience. In two out of four specifications, the effect of peer permanent productivity is completely absent. In Table 7.5 we present results taking into account agents' gender: There are no heterogeneous effects from peer permanent productivity according to gender (female) or to the female proportion in the team. In constract to Table 7.4, the free-riding effect is present in all four specifications. The interaction term in the last two specifications is negative: The presence of females would induce free-riding had the effect been statistically significant (note there are only 10 female agents out of 320). In Table 7.6, we focus on nonlinear effects from peer permanent productivity. Neither the variance of the peer composition in ability nor the square of peer permanent productivity seem to matter for own performance. The free-riding effect stems from the team average alone.

Table 7.4: Peer Effects Models with Interaction Terms in Peer Permanent Productivity and (Peer) Experience – Production with 10 to 20 Agents

	(1)	(2)	(3)	(4)
Peer current productivity	-	0.662**	-	0.666**
		(0.297)		(0.300)
Peer permanent productivity	-0.041	-0.052*	-0.097**	-0.055
	(0.026)	(0.027)	(0.040)	(0.046)
Peer permanent productivity interacted with:				
Own experience×1000	-0.048	-0.065*		
	(0.000)	(0.000)		
Peer experience ×1000			0.096	-0.056
			(0.000)	(0.000)

Note: Dependent variable is (log) number of build-up scans in 1 hour. 11, 116 observations for 273 agents and 177 Saturdays. All specifications include agent and time fixed effects, own and peer experience and their squares, peer gender, peer nationality, peer manager and dummies for production hall. *, ** and *** denote significance at 10%, 5% and 1% level respectively. Specifications under columns (1) and (3) are estimated with OLS; bootstrapped standard errors (1, 000 replications) in parentheses. Specifications under columns (2) and (4) are estimated with 2SLS; bootstrapped standard errors (1, 000 replications) clustered at the agent level in parentheses. Excluded instruments are second order social effects of exogenous variables. Specifications pass tests for underidentification (reject null of underidentification for at level of significance), overidentification and weak instruments (test statistics around 30).

Table 7.5: Peer Effects Models with Interaction Terms in Peer Permanent Productivity and (Peer) Gender – Production with 10 to 20 Agents

	(1)	(2)	(3)	(4)
Peer current productivity	-	0.649**	-	0.690**
		(0.298)		(0.299)
Peer permanent productivity	-0.063***	-0.081***	-0.050**	-0.067***
	(0.020)	(0.022)	(0.021)	(0.023)
Peer permanent productivity interacted with:				
Female	0.129	0.140		
	(0.220)	(0.225)		
Female peers	-		-0.469	-0.553*
			(0.288)	(0.290)

Note: Dependent variable is (log) number of build-up scans in 1 hour. 11, 116 observations for 273 agents and 177 Saturdays. All specifications include agent and time fixed effects, own and peer experience and their squares, peer gender, peer nationality, peer manager and dummies for production hall. *, ** and *** denote significance at 10%, 5% and 1% level respectively. Specifications under columns (1) and (3) are estimated with OLS; bootstrapped standard errors (1, 000 replications) in parentheses. Specifications under columns (2) and (4) are estimated with 2SLS; bootstrapped standard errors (1, 000 replications) clustered at the agent level in parentheses. Excluded instruments are second order social effects of exogenous variables. Specifications pass tests for underidentification (reject null of underidentification for at level of significance), overidentification and weak instruments (test statistics around 30).

Table 7.6: Peer Effects Models with Variance and Square of Peer Permanent Productivity – Production with 10 to 20 Agents

	(1)	(2)	(3)	(4)
Peer current productivity	-	0.664**	-	0.663**
		(0.296)		(0.301)
Peer permanent productivity	-0.068***	-0.092***	-0.060***	-0.089***
	(0.021)	(0.025)	(0.021)	(0.026)
Variance of peer permanent productivity	0.004	0.008*	-	-
	(0.004)	(0.005)		
Square of peer permanent productivity	-	-	0.001	-0.020
			(0.016)	(0.019)

Note: Dependent variable is (log) number of build-up scans in 1 hour. 11,116 observations for 273 agents and 177 Saturdays. All specifications include agent and time fixed effects, own and peer experience and their squares, peer gender, peer nationality, peer manager and dummies for production hall. *, ** and *** denote significance at 10%, 5% and 1% level respectively. Specifications under columns (1) and (3) are estimated with OLS; bootstrapped standard errors (1,000 replications) in parentheses. Specifications under columns (2) and (4) are estimated with 2SLS; bootstrapped standard errors (1,000 replications) clustered at the agent level in parentheses. Excluded instruments are second order social effects of exogenous variables. Specifications pass tests for underidentification (reject null of underidentification for at level of significance), overidentification and weak instruments (test statistics around 30).

In Table 7.7 we present estimated coefficients when we interact peer permanent productivity with own and peer nationality. From columns (1)-(4) we conclude that free-riding does not vary with own nationality, although the interacted effect is negative for native agents and positive for foreign agents (majority). From column (5), we see that if the proportion of native peers is 1, i.e., all peers are natives, then free-riding is eliminated as the total effect amounts to 0.1. Unfortunately, the effect does not linger as we include peer contemporaneous effects in column (6). In column (8), it is obvious that free-riding depends on the proportion of foreign peers (majority) as the effect of peer permanent productivity becomes insignificant. If the proportion of foreign peers (majority) in the shift is 1, then a 10% increase in permanent productivity results in a 2.23% decrease in own perfomance. Notice that the mean permanent productivity of the majority-foreign agents is 0.54 while that of the natives is -0.77, and that of other foreign nationalities is 0.19, i.e., on average the majority-foreign agents have higher ability to consolidate pallets. Our study reveals that when coworkers share the same culture, i.e., when there is a high degree of team homogeneity, then the realized Nash equilibrium is an inefficient one due to reduced strategic uncertainty even if the agents carry a high-productivity signal. One would think that homogeneous teams in terms of nationality and background would achieve a higher level of collaboration, for instance, through communicating with their native language instead of German; in this case, team homogeneity results in feeling comfortable enough with peers so that free-riding becomes a socially acceptable behavior.

7.2 Implications for Optimal Team Composition

We provide evidence on the existence and the complex interplay of endogenous and exogenous social effects among workers. In general, our results suggest that the observed agents care about how they are perceived by their colleagues. Although we find current peer behavior to be more important

Table 7.7: Peer Effects Models with Interaction Terms in Peer Permanent Productivity and (Peer) Nationality – Production with 10 to 20 Agents

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Peer current productivity	-	0.654**	-	0.653**	-	0.652**	-	0.646**
		(0.297)		(0.296)		(0.296)		(0.297)
Peer permanent productivity	-0.057***	-0.071***	-0.087***	-0.112***	-0.114***	-0.118***	0.113*	0.044
	(0.021)	(0.024)	(0.024)	(0.028)	(0.030)	(0.032)	(0.058)	(0.067)
Peer permanent productivity interacted with:								
Natives	-0.013	-0.026						
	(0.033)	(0.034)						
Foreign nationals (majority)			0.049	0.063*				
			(0.034)	(0.035)				
Native peers					0.214**	0.162		
					(0.100)	(0.106)		
Foreign peers (majority)							-0.319***	-0.223**
							(0.094)	(0.104)

Note: Dependent variable is (log) number of build-up scans in 1 hour. $11,116$ observations for 273 agents and 177 Saturdays. All specifications include agent and time fixed effects, own and peer experience and their squares, peer gender, peer nationality, peer manager and dummies for production hall. *, ** and *** denote significance at 10%, 5% and 1% level respectively. Specifications under columns (1), (3), (5) and (7) are estimated with OLS; bootstrapped standard errors ($1,000$ replications) in parentheses. Specifications under columns (2), (4), (6) and (8) are estimated with 2SLS; bootstrapped standard errors ($1,000$ replications) clustered at the agent level in parentheses. Excluded instruments are second order social effects of exogenous variables. Specifications pass tests for underidentification (reject null of underidentification for at level of significance), overidentification and weak instruments (test statistics around 30).

for current individual productivity compared to long-run peer behavior as measured by permanent productivity, both forces have to be taken into account when conducting managerial inferences because of their adverse effectiveness. Another important finding is that the occurrence of peer effects is a function of team size (or spatial proximity). Having this said, what should organizations do?

To exploit peer effects, teams have to be large enough. Only workers who move closely to each other can mutually perceive the presence, the characteristics and the current productivity of their peers. To enforce this, managers should pool several build-ups in one warehouse hall thereby avoiding the distribution of a few agents in different halls. For example, if at a given time in each of the four warehouse halls only a few (e.g., 1, 2, or 3) workers operate in build-up activities, managers should make them work in one hall, therefore, avoiding the agents operating in different halls. Ideally, build-up allocations should be arranged across halls in a way that team size is "sufficient" (i.e., 10 or more agents per hall). As an example, let us assume that 12 agents have to build up 12 pallets. To exploit peer effects, the organization would have to allocate these build-ups in one hall with a team of 12, instead of allocating it, for instance, in four halls with four small teams (e.g., 4 x 3 agents). Although this already happens to a large extend, there is further potential: we find $2,732$ hourly intervals during which at least 10 build-up agents are active in the warehouse. Thereof, in 894 hourly intervals ($32,7\%$) operations are split across halls in a way that team size in every hall is smaller than 10 agents.

Our results imply that endogenous and exogenous social effects operate adversely. In general, managers should aim at exploiting the positive side of endogenous effects, and concurrently avoid possible consequences through negative effects. The latter occur as the free-riding effect on peer ability becomes contagious because of the strong positive dependence in agents' current productivity. As a consequence, (large) shifts should be composed with agents who do not know each other's permanent productivity in order to exploit positive endogenous effects and avoid free-riding through negative permanent productivity effects. If employees do not know each other's ability type then the remaining effect is that of peer current productivity which is positive (in large teams). A concrete example is the introduction of a newcomer who works fast. In that case, average current productivity increases (without changing the workers' perception of peer average permanent productivity) and so does individual productivity because of the positive endogenous effects.

This suggestion may be hard to implement in typical business operations because it requires continuous hires and dismissals. If this is the case, the problem of contagious free-riding through peer imitation within this environment has to be tackled differently. One approach is to set up an efficient wage scheme that minimizes negative social effects. For example, the organization could enhance the fixed-payment structure by individual piece-rate (cf., Lazear, 2000), or team-based components (cf., Babcock, Bedard, Charness, Hartman, and Royer, 2015; Friebel, Heinz, Krueger, and Zubanov, 2017), or a combination of both.[25] Another approach is to decrease information asymmetries on

[25] With respect to the underlying production environment, it is ineligible to abstract from quality aspects at the same time. Hence, the incentive scheme must be balanced with and linked to appropriate quality measures, simultaneously—for example, the offload-ratio.

performances between agents and managers: Additional information about a worker's production behavior, even if imperfect, can lead to improvements (cf., Stiglitz, 1975; Holmström, 1982). This can be reached by the implementation of adequate monitoring mechanisms. For example, firms could introduce an observer who has the authority to give directives and reports directly to the manager. Alternatively, managers could be granted access to the individual performance statistics of their agents (and agents have to know about this).

Moreover, our results provide an example in which team homogeneity leads to the adoption of an otherwise socially unacceptable behavior: free-riding. The latter reaches a maximum when the proportion of majority-foreign peers is 1. When all peers are of the same foreign nationality, agents feel comfortable enough to slow down when they perceive an increase in peer permanent productivity. Therefore, it is crucial to compose teams with a large variation in nationality in order to avoid inefficient equilibria.

8 Conclusions

By exploiting panel data on the performance of warehouse agents, we estimate social interaction effects in the workplace in a way that disentangles endogenous (current) effects and exogenous (permanent) effects. Thereby, we uncover new insights into the interdependence and the mode of operation between these types of effects. We find that the emergence of both endogenous and exogenous effects is a function of team size—only when teams are of a sufficient size (i.e, 10 workers or more work simultaneously), peer effects occur. We ascribe these findings to spatial circumstances and the sense of monitoring: within the warehouse halls, agents in small teams might end up sparsely having no or less opportunities to perceive the behavior of others. With increasing team size the likeliness that agents work closer rises and offers possibilities for social effects. In large teams, endogenous and exogenous effects operate in an adverse way: while a 10% increase in peer current productivity leads to a ceteris paribus increase in own productivity of 6.5%, a 10% increase in peer permanent productivity decreases own productivity by 0.78%. The magnitudes of the effects imply that peer behavior with respect to current productivity matters more than permanent productivity. If all peers are from the same foreign nationality that comprises the majority of warehouse agents, then a 10% increase in peer permanent productivity decreases own productivity by 2.23%, pointing to the importance of heterogeneous teams with respect to nationality and culture. In order to exploit efficiently the positive side of endogenous effects, management should compose large enough shifts with agents who do not know each other's ability type, have diverse nationalities and resort to adequate monitoring mechanisms—for instance, by introducing authorized observers.

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