Compositional Peer Effects in Team Production

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I examine peer effects among workers at a large cargo warehouse. For estimation purposes, I adopt the econometric model from Mas and Moretti (2009). Using individual performance data on cargo palette consolidations, I find evidence for the emergence of compositional peer effects among warehouse agents. Magnitudes of peer effects vary across warehouse agents, but sensitivity in responsiveness does not depend on warehouse agents' levels of permanent productivity.

Peer effects are a substantial motivational force in industrial production. Hence, whether and how a worker's productivity depends on the productivity of his colleagues is still a very topical question in behavioral economics. As shown theoretically by Kandel and Lazear (1992), peer effects may not only raise workers' productivity, they also can potentially contributing to overcome the free-rider problem. Thus, peer effects represent a form of social incentive reducing the gap of an incomplete contract when no effort based compensation is in place.[1] For an organization, knowing about the existence, magnitudes and mechanisms of peer effects among agents is advantageous in order to optimize both working incentives and long-term shift compositions.

Although the list of academic papers on the topic of peer effects is long, there are only a few field studies examining peer effects in a workplace environment.[2] The general idea of these research articles is that subjects enhance productivity when working with more productive peers. While some papers provide evidence on the existence of peer effects, others do not find significant results.[3] The

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[1] Guryan, Kroft and Notowidigdo (2009) rightly point out that – in order to create an efficient incentive scheme – an organization must be aware of whether peer effects are substitutes or complements for financial incentives.

[2] On the one hand it seems problematic for academic researchers to get access to worker specific performance data of a firm (Bartel, Ichniowski and Shaw, 2004). On the other hand, the data security policies of organizations encumbers an academic analysis of such data.

[3] Falk and Ichino (2006) present one of the first empirical studies giving evidence on the existence of peer effects in a laboratory setting. In the field, among others, Ichino and Maggi (2000), Kato and Shu (2008), Mas and Moretti (2009) as well as Bandiera, Barankay and Rasul (2010) prove the existence of peer effects within a specific settings. In contrast to these papers, Guryan, Kroft and Notowidigdo (2009) as well as (Waldinger, 2012), for instance, find no evidence on peer effects.

emergence and the magnitude of potential peer effects in real workplace environments vary across individuals, working environments and incentive schemes. For a better understanding of peer-effect mechanisms and in order to shed more light on potential causes of peer effects in the workplace further field studies in different organizational environments and on different subjects are required.[4] For this purpose, access to high-frequency organizational data on individual productivity is crucial.[5]

This paper complements to the existing literature on peer effects in the workplace. I investigate peer effects among warehouse agents at a freight forwarding company who consolidate items onto palettes. My empirical analysis is based on long-term productivity data of 175 warehouse agents. The underlying operational process is prone to free-riding since individual output is not observable by managers and warehouse agents are paid fixed wages. For a warehouse agent it seems rational to dump his workload onto co-workers. Since these environmental characteristics of build-up operations are similar to the setting in Mas and Moretti (2009), I adopt the corresponding econometric model for estimation purposes assuming social pressure (Kandel and Lazear, 1992) as the underlying motivational force provoking peer effects. By doing this, my analysis contributes to a better evaluation of the question whether the results from (among others) Kandel and Lazear (1992) as well as Mas and Moretti (2009) can be generalized and transferred to both different subjects and working environments.

My results provide evidence on the existence of positive compositional peer effects in this specific working context: A 10 percent increase in average coworker permanent productivity is related to a 1.6 percent increase in current productivity of the focal worker, on average. Moreover, the data provides evidence for differences in peer-effect magnitudes across considered warehouse agents. However, these differences in responsiveness can not be explained by different levels of permanent productivity.

The paper is organized as follows. The next section presents a literary outline of relevant academic articles on peer effects in the workplace. Section II describes the considered operational process and underlying incentive scheme as well as my measure of productivity. Sections III, IV and V illustrate the empirical framework, the underlying data set and my findings. Section VI concludes.

I. Related Literature

There is a long list of literature on the topic of peer effects, and scientific work goes back to the end of the 19th century. Triplett (1898) is known as the first who gave evidence on the basic idea that individuals' performances might be

[4] Guryan, Kroft and Notowidigdo (2009) "*hope* [that] *our findings will spur other researchers to further explore* [...] *peer effects in the workplace.*"

[5] Bartel, Ichniowski and Shaw (2004) speak about "*Insider Econometrics*"—an approach of econometrically conducting empirical studies on organizations based on the appropriate data. Griliches (1994) argues this method to be necessary since "[the] *advances* [which] *have been made in theory and in econometric techniques* [...] *will be wasted unless they are applied to the right data.*"

affected by other present individuals. He studied cyclists and found that athletes were faster under competition with other athletes, and slower when racing against the clock. These findings are abstracted with the term *social facilitation*[6]: Triplett (1898) argued theoretically that the mere presence of other subjects has a positive effect on individuals' performances—that is, performance might be *facilitated*. However, there are other studies proving that the performance of an individual might also be lowered by the presence of other subjects (Husband, 1931; Pessin, 1933). Zajonc (1965) theorizes that these opposed effects result from the variety concerning a task's complexity: While for simple and well-practiced tasks the mere presence of other individuals enhances productivity of the focal subject, for complex and difficult tasks the presence of others inhibits performance.[7]

Especially in the last decades, economic research studies on the topic of peer effects emerged, whereupon different domains are covered, Among others, there are analysis in education (Burke and Sass, 2008; Sacerdote, 2001), in science (Waldinger, 2012), in crime (Glaeser, Sacerdote and Scheinkman, 1996; Gould and Kaplan, 2011), in shirking (Ichino and Maggi, 2000) and within organizations (Falk and Ichino, 2006; Kato and Shu, 2008; Mas and Moretti, 2009; Bandiera, Barankay and Rasul, 2010). Whereas all of these papers are relevant for understanding peer effects, especially the latter are important when examining peer effects in the workplace.

Falk and Ichino (2006) published the first empirical study on peer effects in a work-like environment. Their analysis is based on a controlled laboratory experiment. Students were asked to fill letters into envelopes. In exchange, they get a fixed payment that is independent on individual output. In the "single treatment" students work alone, and there is no potential for the occurrence on peer effects. In the "pair treatment" two students independently work on the task sitting in the same room, and peer effects are possible. In their analysis the authors find evidence of peer effects because average individual performance in the "pair treatment" significantly exceeds average individual performance in the "single treatment". When working within pairs, a 10 percent increase in output of a subject's peer is related to a 1.4 percent increase in output of the given subject. The authors interpret the estimated magnitude of the peer effects as a lower boundary for peer effects that prevail in real-life working environment, because subjects' did not know each other and interacted only once.

Mas and Moretti (2009) examine peer effects in a real-life workplace setting. By using high-frequency field data on the productivity of supermarket cashiers the authors provide evidence on the existence of peer effects. Peer Effects appear

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

[7]As a result of its *emotional activation* a subject primary reacts with its *dominant response* when others are around. From a set of competing reactions the dominant response of an individual is defined as the reaction, that is most likely to occur for the concerned subject in a given situation (e. g. well-learned or instinctive reactions). For instance, a student taking an oral exam very probably stands under psychologixal pressure. He probably gives an incorrect answer, when the correct answer was learned recently and the incorrect one was deemed to be the correct answer for a long time—because for this student the incorrect answer is still the dominant response (Zajonc, 1965; Cottrell et al., 1968).

as productivity spillovers caused by social pressure. The estimated magnitudes of peer effects are in line with those provided by Falk and Ichino (2006): A 10 percent increase in the average permanent productivity of co-workers is related to a 1.5 percent increase in focal worker's productivity. These findings seem surprising because the analyzed 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 co-workers' performance—for a cashier it seems rational to unload one's workload onto co-workers. However, the possibility of monitoring each others' output causes positive peer effects since cashiers react on emerging social pressure by 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.

Another related field study by Bandiera, Barankay and Rasul (2010) combines 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: Considered subjects tend to conform to the productivity level of their friends when mutual monitoring is possible. Again, this implies that co-workers' output affects focal worker's output.

Exploiting individual data of weavers on defect rates in a textile manufacturer Kato and Shu (2008) also provide evidence on peer effects caused by performance spillovers through unidirectional knowledge sharing from high-ability weavers to low-ability weavers. In a subsequent working paper, the authors also show that weavers perform better when interacting with more productive outgroup peers but not when interacting with more productive ingroup peers, and prove intergroup competition as a further possible source of peer effects (Kato and Shu, 2009).

Despite that a couple of field studies providing evidence on peer effects in workplace contexts, emergence is not a matter of course. Guryan, Kroft and Notowidigdo (2009) use explicit random groupings of elite golf players to test whether peer effects exist in the context of professional golf tournaments. They show that peer effects do not emerge within this setting. Also Waldinger (2012), who analyses a data set on the historical research performance of natural scientists, finds no evidence for peer effects (on a local level) in his study. Moreover, he shows that even researchers with very high ability do not affect the output of their peers.

This literature outline indicates that emergence and magnitude of peer effects in real workplaces vary across subjects, across the context of work and across the applied incentive schemes. Not least because of this ambiguity, further field studies in different organizational environments, and on different personalities are necessary in order to better understand peer-effect mechanisms, and to shed more light on potential sources of peer effects in the workplace. Motivated by these findings, I examine peer effects in another labor environment. In the next section, I describe the corresponding setting, the working process, the applied incentive scheme as well as my defined measure of productivity.

II. Environmental Characteristics

A. Production Process

My empirical research is based on a worker-specific data set on the productivity of warehouse agents who perform freight palette build-ups—that is, they consolidate cargo items on loading devices. Based on a palette-specific build-up plan, warehouse agents consecutively pick up designated shipment items[8] with a forklift and load them onto a build-up unit. The corresponding shipment items are already procured in front of the designated palettes before the build-up starts. Usually, several pallets are built up simultaneously by the warehouse agents . A single palette is built up by at least one agent. Efforts of single agents are not multiplicative but substitutable.[9] All movements of shipment items are captured by barcode scanners (provided with a personal log-in) and are consistently stored in the corresponding data base of the warehouse management system.[10] When all pre-planned items are loaded onto the palette, the scanner prompts a dialogue to inform the agent that the build-up palette is finalized. If a warehouse agent assigns a shipment item to a wrong palette, the barcode scanner prompts an error dialogue. That is, assignments of items to wrong palettes are prevented by the warehouse management system.

In forwarder business, the build-up process is seen as the most crucial activity because it is subject to the highest time pressure: While freight delivery for a certain palette usually takes several days, the consolidation itself has to be performed within a few hours, because – according to regulations – build-ups start, when all 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, the latest acceptance time of an export shipment is only a few hours before estimated build-up completion (which itself is determined by successor transport schedule). In practice, shipment delivery usually is completed only a few minutes before LAT, since supply chain members seek to minimize overall cycle time. Hence, the freight 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 probably be make up during the overall process, a build-up which is too late, no matter what, will lead to an offload of the whole palette from it's planned outgoing transport (that is, each associated item). Not only that the affected shipment items have to be re-planned and re-booked on other successor transports by sales department, but also transport planning (capacity steering and loading sequence) has to be adjusted on short notice. Moreover, an offload may lead to contract penalties, and it may result in damage to the company's image.

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

[9] This implies, that – under joint production (i. e. more than one warehouse agent working on a single palette) – considered subjects cannot exploit complementaries in order to achieve a higher level of output compared to their peers (De Giorgi and Pellizzari, 2011).

[10] Illustrations of the production area as well as working equipment are placed in the appendix.

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 palette 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, palette consolidations can be interpreted as enhanced *Knapsack Problems*[11] with many constraints imposing above average requirements on agents' combinatorial ability.

B. Measure of Performance

Many empirical studies use aggregated measures of performance, because in most cases access to individual productivity data for research purposes is not provided by organizations. Usually, these studies use productivity data on firm level or sector level. These productivity measures are improper for estimating peer effects because they do not emerge on an individual basis. During the recent decades, studies emerged, using productivity data on a worker level or shift level (c. f. section I). I also have access to long-time performance data on an individual level. I rely on worker-specific scanner data of warehouse agents who perform palette build-ups. Each movement of a shipment item is captured by the responsible warehouse agent with the help of a barcode scanner. All scanner transactions are stored historically in a data base of the warehouse management IT system. As the measure of current individual productivity, I define the number of pieces contributed to any build-up unit by warehouse agent i over a one-hour time period t, y_{it}. In cargo handling processes the number of pieces is the essential measure of performance, because it is seen as the major effort driver. This measure is observable, comparable for a single warehouse agent over time, and comparable across different warehouse agents within one period and over time.

The data I use is precise and collected on a worker-specific level: Since every warehouse agent has his own scanner sign-in, there is always a valid linkage between an item movement transaction and the executing warehouse agent. All transactions are stored in the data base of the warehouse management system, without gaps. Hence, it is easily possible to identify changes in current individual productivity. By using this type of data I 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 IT system and requirements of security guidelines are high, measurement errors are expected to be rare. Nevertheless, this performance figure also has weaknesses, because it does not cover an exact measure of work quality:

[11] The *Knapsack Problem* (also: *Rucksack Problem*) is an NP-complete optimization problem: Out of a given set of items, each with a weight, a volume and a value, those items have to be chosen into in a way that the overall value of the collected items is maximized without exceeding the knapsack's capacity (and – in some cases – other corresponding constraints) (Karp, 1972; Martello and Toth, 1990).

Shipment items, which are built up improperly, have to be broken down and corrected—for example, the affected items have to be removed from a palette, and re-ordered on a different build-up unit.[12] Moreover, it is hard to control for the experience of a worker in operating a forklift. As mentioned above, nearly all shipment items are built up with the help of a forklift, and its usage is essential for build-up speed and quality. For control purposes, I use a proxy in my estimations reflecting general experience of warehouse agents.[13] Another weakness of the used productivity measure is the impossibility of determining temporary worker absenteeism during a one-hour interval: For example, it may be the case that warehouse agents perform tasks in the beginning and at the end of a one-hour time period, but not between these times.

C. Shift Scheduling

Production is performed 24/7, and operations are organized in shifts work. Each day, four *work shifts*[14] 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, form 2:00 pm until 11:30 pm in the late work shift, and from 22:00 pm until 6:30 am in the night work shift. Moreover, there is a day work shift from 09:30 am till 18:00 pm where only a few warehouse agents are planned for. From the defined core times it becomes clear, 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. Often, overlapping periods are longer than 30 minutes: Because the working contract 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 more than two hours.

Assignment of workers to shifts is not explicitly random. Management is responsible for scheduling, and planning takes place several weeks in advance. Due to negotiated rules and individual leeway, scheduling can be seen as unsystematic: Shift compositions change permanently—there are no fixed teams. Additionally, the number of warehouse agents working in a shift changes. On the one hand, shift compositions depend on the availability of colleagues, which is restricted by negotiated free time rules and vacation rules as well as other forms of absenteeism, e. g. due to illness. On the other hand, shifts are planned on the basis of expected demand. Management has no ambition to assign the most productive warehouse agents to the busiest shifts.

[12] An improperly built up item, for instance, is an item overhanging the contour of a palette. However, an improperly built up item does not characterize wrong assignments of shipment items to palettes—as described above, this does not happen, because the barcode scanning software checks all build-up transactions against the corresponding build-up planning on a palette-level and prompts an error dialogue in case of a deviation.

[13] I assume that the individual experience in general handling is highly correlated with the individual experience in operating a forklift.

[14] In the context of this paper, the term work shift represents a whole working shift with a duration of 8.5 hours (breaks includes). The term *shift*, however, describes a one-hour period, t, and is used for estimation reasons.

Note that – from an econometrical point of view – a haphazard co-worker composition within a considered one-hour time interval, t, is more important than scheduling of 8.5-hour work shifts. Per se, the environmental setup described above does not rule out sorting of agents during a one-hour time interval. The second crucial question is how workers are assigned to single build-up palettes. As stated above, in some cases more than one warehouse agents works on one and the same palette. For a valid identification of peer effects, endogenous sorting has to be ruled out—i. e. if more than one worker proceeds on a single palette, this team constellations has to haphazard. Both issues are addressed in section III. I show, that sorting is not a problem.

D. Incentive Scheme

All observed workers gain a fixed wage plus holiday premium and shift allowance. No effort-based compensation payment element is applied. In fact, an incomplete contract exists in this working environment: Working contracts neither contain requirements for effort (only weekly normal working time is specified), nor explicit performance goals. Furthermore, no relationship 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 effort-based premiums depending on the fulfillment of pre-defined target agreements.

Managers are unable to perfectly observe the individual output contribution of single warehouse agents. This results from several factors, e. g., building floor space, 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 represents a disadvantage, because the fulfillment of their individual targets depends to a substantial extend on the performance of their employees.

Overcoming the lack of observability is impossible, because agency costs are too high. 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. Due to this, the whole team is held to account when performance is weak. Information from managers and warehouse agents, therefore, is asymmetric, and an *agency problem* exists.[15] Thus, 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 his 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. Reduced effort by an agent in relation to his peers may result in resentment or sanctions from his co-workers. Due to this, it is optimal for a worker to contribute a fair share, and work harder, reducing the productivity gap with his more productive peers (Kandel and Lazear, 1992; Mas and Moretti, 2009).

[15] Besides an agency problem, a *problem of risk sharing* exists, because the risk appetites of managers and warehouse agents are expected to differ. Though, the problem of risk sharing is not considered in the context of this paper.

E. Expectations on the Existence of Peer Effects

As described in the previous section the reduction of a single worker's effort seems rational to him at first, but it also imposes negative externalities on his peers, because they have to work harder in order to finalize a palette consolidation in time and avoid any offloads.Build-ups take place on two levels in a warehouse. On both levels, an area of around 4.000 square meters is dedicated for shipment consolidation. Warehouse agents move freely within the warehouse, having the possibility to monitor each other. Additionally, they can trace the progress of each active build-up (including the name of the warehouse agent who executes a certain build-up) on monitors near to the pallet build-up stations and with the help of mobile devices. Moreover, they are informed about the status of active and completed build-ups by other agents. This implies that the information is distributed quite symmetrically among the warehouse agents. Because, warehouse agents are able to assess the activities of their colleagues, an effort reduction of a single worker is expected to cause resentment or the agent is likely to face sanctions from his peers, because it represents a deviation from the established working norm and imposes negative externalities on the peers (Kandel and Lazear, 1992; Falk and Ichino, 2006; Kato and Shu, 2008; Mas and Moretti, 2009). For each warehouse agent, performing a fair share of the work, therefore, is the expected reaction. For a single warehouse agent, this implies to work harder when more productive colleagues are around in order to reduce the relative productivity gap with his more productive peers. As shown theoretically by Kandel and Lazear (1992) and empirically – among others – by Mas and Moretti (2009) social pressure describes a mechanism for peer effects in the workplace when mutual monitoring among workers is possible.[16] Mas and Moretti (2009) define social pressure as "*encompassing cases where workers experience disutility if they are observed behaving selfishly by their peers*". The authors conclude, that social pressure partially internalizes the described externalities many workplace settings are typical for.

For the described working environment I expect peer effects among the considered warehouse agents to be existent. Since environmental characteristics are similar to Mas and Moretti (2009) in many points[17], I also assume social pressure being the dominant mechanism driving the existence of peer effects. Adopting the estimation model of Mas and Moretti (2009), I empirically examine the emergence of peer effects in the described setting.

[16] De Giorgi and Pellizzari (2011) find mutual insurance among agents another possible mechanism describing behavioral changes through social interactions. The authors state that mechanisms depend on the setting and environment.

[17] In both settings output determination by managers is impossible, but workers, among themselves, are well informed of the current productivity of their peers (due to possibility of mutual monitoring). Thus, reducing one worker's effort is expected to induce negative externalities on his colleagues since they have to work harder to maintain the level of overall shift output. Moreover, reducing one's effort is expected to be interpreted as a deviation from established working norms by peers, resulting in resentment or sanctions. Hence, analogous to the setting of Mas and Moretti (2009), social pressure is likely to be present in build-up operations.

III. Empirical Framework

A. Identification

In general, peer effect exist if the behavior of individual i changes through a ceteris paribus change in individual's j behavior. Falk and Ichino (2006) deduce a more specific defintion of peer effects in a workplace environment: "[positive] *peer effects exist if the output of individual i increases when the output of j increases and nothing else changes*". For considered build-up operations, this implies that peer effects are present if a warehouse agent's current productivity is influenced by the current productivity of his peers (that is, how hard his peers perform at time t). Kato and Shu (2008) summarized this type of peer effect with the term *contemporaneous peer effects*. Another approach for identification of peer effects is to assume that the current output of a warehouse agent depends on the permanent productivity of his peers (that is, how capable his peers are), rather than on peers' current productivity—this type of peer effect is named *compositional peer effects* (Kato and Shu, 2008).

Contemporaneous Peer Effects.—From an economical point of view, both identification theories are interesting. However, the identification of contemporaneous peer suffers from the reflection problem (Manski, 1993): Because the productivity of warehouse agent i in period t influences the productivity of warehouse agent j in period t and vise versa, the reason for a change in a worker's productivity cannot be determined with this identification strategy since the direction of causality cannot be identified—among warehouse agents an endogenous interaction effect exists.[18] Another disadvantage of this identification method is that it is prone to spurious relationships: If in period t a shock (e. g. unexpected increase of freight volume or ad-hoc orders) occurs, both current productivity of warehouse agent i and current productivity of his peers are likely to increase simultaneously, which results in a spurious correlation—whereby the reason for the increase in current productivity is not due to peer effects but an external shock.

Compositional Peer Effects.—To identify compositional peer effects it is assumed that a change in focal warehouse agent's current productivity is caused by a change in average co-worker permanent productivity due to steady variation in team composition. This approach does not suffer from the reflection problem, since neither the error term nor the current productivity of the focal worker influences the average permanent productivity of his peers (Kato and Shu, 2008). This identification strategy firstly was applied by Sacerdote (2001)

[18] In this case a simultaneous relationship between dependent and independent variables exists, because both groups of variables influence each other. This implies a potential correlation of the independent variables and the error term in the OSL regression. Estimates would be biased and estimation would not be efficient (Manski, 1993). In order to solve this problem and to ensure a valid identification of contemporaneous effects, an instrumental variable is required that influences the average current productivity of a co-worker while not affecting the focal worker's current productivity. However, such an instrument does not exist by definition since every worker is a co-worker of his colleagues within the same time period (Kato and Shu, 2008; Mas and Moretti, 2009).

and is favored among authors of recent peer effect publications, e. g. Kato and Shu (2008), Mas and Moretti (2009), Guryan, Kroft and Notowidigdo (2009) as well as Bandiera, Barankay and Rasul (2010). In this paper, I also rely on this established approach to identify compositional peer effects rather than contemporaneous peer effects.

B. General Assumption

I assume peer effects to be present among warehouse agents. Warehouse agents are expected to berform better when working with more able peers. Since setting characteristics of build-up operations are similar to the examined working environment of Mas and Moretti (2009), I also expect social pressure to be the dominant mechanism driving the existence of peer effects.

C. Production Function

Assume the following production function (Mas and Moretti, 2009):

$$y_{it} = f\left(\theta_i, P_{it}, N_t, \delta_{dh}, \epsilon_{it}\right), \tag{1}$$

where y_{it} is the productivity of warehouse agent i in period t (current productivity), θ_i is warehouse agent's i time-invariant innate ability (permanent productivity), P_{it} represents an (unknown) function for social pressure exerted on i by i's peers in t, N_t is number of present workers in t, δ_{dh} is a set of dummies for day of week and hour of day combination, and ϵ_{it} is the error term capturing unobservable factors. The index t represents a on hour-time interval (shift). Whereas y_{it}, N_t and δ_{dh} are directly observeable through the data, θ_i and P_{it} are not. Hence, θ_i and P_{it} have to be determined.

D. Mathematical Representation of Social Pressure

P_{it} represents a function for social pressure and is notated

$$P_{it}\left(\Theta_{it}\right), \text{ with } \Theta_{it} = \left\{\theta_j | \forall j \text{ active in period } t, j \neq i\right\}. \tag{2}$$

The social pressure function 2 is adopted from Kandel and Lazear (1992). I assume that social pressure on warehouse agent i in period t depends on the permanent productivity of i's peers (in t), but not on the permanent productivity of i himself. Θ_{it} is a defined set containing permanent productivities of warehouse agents who are active in period t (excluding warehouse agent i). While $\theta_j \in \Theta_{it}$ (if warehouse agent j is active in period t), $\theta_i \notin \Theta_{it}$.[19]

[19] In its basic functional design defined by Kandel and Lazear (1992), $P_{it}()$ depends on performances as well as actions of all workers within a team (including worker i). The function is notated $P\left(e_i, e_1, \ldots, e_N, a_i, a_1, \ldots, a_N\right)$. Initially, the authors assume that social pressure excerted on worker i depends on his own effort, e_i, the effort of his peers, $e_1, \ldots, e_N$, and other unobserved actions, $a_i, a_1, \ldots, a_N$, worker i and his peers exercise. However, Kandel and Lazear (1992) discuss that actions do not have a direct impact on the output within a

Analogous to Mas and Moretti (2009), I proceed to describe a situation where social pressure is parameterized as a function of the average permanent productivities of present co-workers. This parameterization is necessary since the functional form of $P_{it}()$ is undetermined.

$$P_{it}(\Theta_{it}) = \frac{1}{N_t} \sum_{i \neq j} \theta_j = \bar{\theta}_{-it}. \tag{3}$$

$\bar{\theta}_{-it}$ represents the average permanent productivity of all warehouse agents who are active in period t, while the index $-i$ signalizes, that the average value of the permanent productivity, $\bar{\theta}_{-it}$, is computed without using the permanent productivity of the focal warehouse agent i, θ_i. N_t is the number of warehouse agents active in period t.

E. Estimation Approach

According to econometric models of related studies examining compositional peer effects, I implemented a two-step estimation procedure. First, I predict the permanent productivity of each subject. Second, I perform the estimation of peer effects. For the rest of this section, peer effects, from this point on, always mean compositional peer effects.

Step 1: Predicting a Worker's Permanent Productivity.—As described above, the identification of peer effects in this paper relies on the approach of compositional effects assuming that a change in average co-worker permanent productivity causes a change in focal warehouse agent's current productivity. Since I postulate social pressure to be the driving force of peer effects among warehouse agents, this identification approach is realized through a parameterization of the social pressure function 3 with $\bar{\theta}_{-it}$. For calculating $\bar{\theta}_{-it}$, the estimation of the θ_i's is required. In particular, the θ_i's are worker-specific effects, representing heterogeneity across the observed individuals, and can be interpreted as a warehouse agent's innate time-invariant ability (permanent productivity). Estimation is done analogous to Mas and Moretti (2009) using the following fixed effects model:

$$y_{it} = \theta_i + \mathbf{A}'\Phi_{Ci} + \gamma N_t + \delta_{dh} + \epsilon_{it}. \tag{4}$$

θ_i is a worker-specific fixed effect representing the time-invariant permanent productivity of warehouse agent i.[20,21] To account for co-worker composition,

shift. In equation 3, e are parameterized with θ, a is not parameterized.

[20]The θ_i's are unobserved, time-constant random variables, predicted as fixed effects. The key assumption for identification is a random assignment of subject (dummies) conditional on the other independent variables and on the fixed effects (conditional independence assumption). That is, strict exogeneity is assumed. This assumption is relatively strong, because – in the context of the underlying production process – it implicitly requires a random assignment of warehouse agents to one-hour time intervalls, t. As indicated later on, worker compositions in t can be seen as haphazard. Thus, fixed effects estimators are consistent.

[21]In many cases, fixed effect estimators may be subject to large measurement error and, hence, attenuation bias. Because the data is captured by a highly available IT system and

assumed to influence the current productivity of a warehouse agent, the vector Φ_{Ci} is included in the group of regressors. This term enables controlling for all possible (and observed) compositions of build-up workers. Corresponding to Mas and Moretti (2009), Φ_{Ci} absorbs the social pressure function and is derived from the set $\{C_{i1}, \ldots, C_{ik}\}$, where $C_{il} = 1$ if warehouse agent l is active in build-up at period t, $C_{il} = 0$ if $i = l$ and $C_{il} = 0$ if warehouse agent l is not active in build-up at time period t.[22] For every member of Φ_{Ci}, the vector $\mathbf{A}$ contains a specific estimation parameter. With the help of this shift composition term, it is possible to account for the focal warehouse agent's productivity response when working with a specific set of co-workers (Mas and Moretti, 2009). N_t characterizes the number of workers on duty in time period t (including worker i). δ_{dh} is an interaction vector of all possible combinations of weekday d and hour of day h. ϵ_{it} is the error term. θ_i is interpreted as the permanent productivity (innate ability) of warehouse agent i. Warehouse agents with a high θ_i are on average more productive than warehouse agents with a low θ_i.[23]

To estimate the θ_i's, I regress log current productivity of warehouse agent i in period t on a vector of entity-fixed effects, θ_i, a set of dummies representing a specific co-worker shift constellation, Φ_{Ci}, as well as a set of dummies for day of week and hour of the day combination, δ_{dh}.

Using the estimated fixed effects, θ_i, the measure of average co-worker productivity in every one-hour time interval (and for every worker), $\bar{\theta}_{-it}$, is calculated. With the help of these predictions, estimation of the peer effects is possible.

Step 2: Estimating Peer Effects (Baseline).—The following model – which is deviated from function 1 – linearly describes the current productivity of worker i in period t, y_{it} (Mas and Moretti, 2009):

$$y_{it} = \theta_i + P_{it}\left(\Theta_{it}\right) + \gamma N_t + \delta_{dh} + \epsilon_{it}. \tag{5}$$

$P_{it}\left(\right)$ represents the social pressure function described above. Due to parameterization of $P_{it}\left(\right)$ with $\bar{\theta}_{-it}$, the combination of equation 3 and equation 5 yields

$$y_{it} = \theta_i + \beta\bar{\theta}_{-it} + \gamma N_t + \delta_{dh} + \epsilon_{it}. \tag{6}$$

Because I proceed to predict the change in production behavior as a result of a changing shift composition (in order to determine peer effects), model 6 is adopted by taking first differences between t and $t-1$, that is, $\Delta y_{it} = y_{it} -$

security requirements are strict, measurement errors are unlikely. Another point is the fact that the underlying panel data set is unbalanced which also justifies usage of a fixed effects model at this stage.

[22] For each observed co-worker shift composition, a unique dummy is created. Hence, this term not only controls for the mere presence of a warehouse agent's colleagues, but for their composition as well.

[23] Team compositions change permanently. Hence, including potential team fixed effects is gratuitous.

$y_{i(t-1)}$.[24] The underlying assumption is $\mathrm{E}\left(\epsilon_{it}|\theta_i, \bar{\theta}_{-it}, N_t, \delta_{dh}\right) = 0$.

$$\Delta y_{it} = \alpha + \beta \Delta \bar{\theta}_{-it} + \gamma \Delta N_t + \delta_{dh} + \epsilon_{it}. \tag{7}$$

Model 7 describes my baseline equation which is very similar to the corresponding estimation model from Mas and Moretti (2009). In particular, I regress the delta of log current productivity of warehouse agent i between t and $t-1$, Δy_{it}, on the delta of average co-worker permanent productivity between t and $t-1$, $\Delta \bar{\theta}_{-it}$, the delta of number of active workers between t and $t-1$, ΔN_t, and a set of dummies for day of week and hour of the day combination, δ_{dh}. β is the coefficient of interest. It estimates the effect of a change in average permanent co-workers' productivity, $\Delta \bar{\theta}_{-it}$, on worker i's current productivity, Δy_{it} (spillover effect). If peer effects, in general, exist, β is significantly different from zero. If $\beta < 0$, a warehouse agents tends to free-ride if the average permanent co-worker productivity rises from one period to the next. This is caused by a change in co-worker composition (e. g. an entry of one or more warehouse agents with above shift average productivity or an exit of one or more warehouse agents with below shift average productivity). If $\beta > 0$, positive peer effects (in form of productivity spillovers) are present, since an increase in the average permanent co-worker productivity leads to a higher current performance of the focal warehouse agent. In the absence of peer effects, $\beta = 0$.

Using a model in first differences is adequate for the underlying high-frequency performance data. It is well-suited for evaluation of instantaneous effects because of the possibility of accounting for timing of a change in co-workers' average permanent productivity through changes in co-worker compositions between subsequent periods. I assume that a change in co-worker composition in period t causes effects on the productivity of the focal worker in the same period. This assumption is plausible, because warehouse agents are able to evaluate the permanent productivity of their colleagues—that is, they have relieable information who typically is a fast worker and who typically is a slow worker, and adjust their current productivity correspondingly, irrespective of their speed at a particular point in time Mas and Moretti (2009).[25] Only if information about warehouse agents' innate abilities is distributed symmetrically among warehouse agents, an instantaneous reaction can occur (according to the specified model). Otherwise, workers would need some time for gaining information about co-worker's abilities—for example, by mutual monitoring. Indeed, peer effects could be caused by entries of colleagues with unknown permanent productivity (Ichino and Maggi, 2000). However, these effects are not predictable with the specified estimation model 7, since they would not be caused by peer pressure, but through other mechanisms.

To evaluate a peer's permanent productivity, a period of getting to know each other is required (Ichino and Maggi, 2000; Gould and Kaplan, 2011). The

[24] For indification of β, Mas and Moretti (2009) use only variation within a given day for a given worker. Since freight consolidation is processed 24/7, this restriction is not needed.

[25] This is a mandatory requirement for validity of the specified empirical model.

underlying dataset captures warehousing activities from October 2010 until August 2012. Operations were brought on line in December 2009. Hence, most agents worked together for at least ten months in prior[26]. Additionally, many warehouse agents know each other from working activities before December 2009 when they were appointed to other warehouses of the corresponding freight carrier.

Peer effects estimation is processed under the assumption that the permanent productivity of co-workers entering and exiting one-hour-shift periods are uncorrelated. As already indicated prior, a haphazard co-worker composition within a considered one-hour time interval, t, is important for a valid identification. Per se, the environmental setup cannot certainly rule out sorting of agents during a one-hour time interval although scheduling is unsystematic. To address this issue I examined the variation in co-worker composition along t. Overall, I observe $28,774$ different co-worker shift group compositions within $33,043$ observations implying an unsystematic character. Mainly, there are three reasons implicitly explain this large variation. First, it is caused by a haphazard scheduling approach. Second, working shifts overlap for at least 30 minutes four times a day. Third, highly volatile freight volumes throughout a day lead to variations of worker compositions with regard to a one hour production period t.

In $10,874$ out of $83,091$ single build-ups (i. e. around 13 percent), more than one warehouse agent works on one and the same build-up unit.[27] For this case, an endogenous selection of the "teams" has to be ruled out in order to avoid, that the estimated peer effects might be the result of workers choosing to work together for a certain palette.[28] By analyzing absolute and relative frequencies of all observed palette-specific team constellations, I can show that in only two percent of all palette build-ups ($83,091$), a team worked together for more than ten times which indicates that there is also no systematic sorting—even when considering palette-specific build-ups with more than one active worker.[29]

When estimating model 7, standard errors have to be adopted for two reasons: First, because of differencing, serial correlation in the differenced standard errors are likely. Second, since the covariate $\bar{\theta}_{-it}$ itself is calculated by estimates of the fixed effects model 4, standard errors should be adjusted to take into account the sampling variability of $\bar{\theta}_{-it}$. According to the estimation procedure of Mas and Moretti (2009), standard errors are bootstrapped.

IV. Results

This section presents the data set and provides the estimation results of the specified models. First, I describes the underlying panel data. Second, I present the predicted permanent productivities (θ_i) of the observed warehouse agents. Third, I estimate the existence and magnitude of peer effects by examining

[26] Exceptions are new hired colleagues.

[27] The corresponding statistics are illustrated by Table 5 in the Appendix.

[28] Partially this is already addressed through eliminating the fixed effects, θ_i, by taking first differences (equation 7).

[29] The corresponding statistics are illustrated by Table 6 in the Appendix.

Table 1: Descriptive Statistics

	μ	σ	Min	Max	N
Individual Productivity per Hour	24.8	28.5	1	155	39,446
Overall Individual Productivity	12,537.8	9,470.9	338	38437	39,446
Number of Build-Up Workers	6.2	4.1	2	22	39,446
Tenure in Days	477.5	199.4	17	694	39,446
Number of Working Shifts	130.2	73.9	7	295	39,446
Is Shift Supervisor	0.021	0.144	0	1	39,446

Notes: μ indicates means, σ symbolizes standard deviations, N is the number of observations. Individual productivity is the number of shipment items contributed to build-up by a warehouse agent in a one-hour time period. This variable has been winsorized at the 1 percent and 99 percent levels. I included only those one-hour periods during which scanning transactions of at least two build-up agents occured on one floor. Records for warehouse agents, who are observed in less than 30 periods, are excluded. Overall individual productivity represents the sum of built up pieces over all time periods during which a warehouse agent was active. Transactions done for correction processes are also excluded.

whether and how coworkers' permanent productivity influences a worker's current output. Finally, I enhance my model to analyze heterogeneity of peer effects depending on the agents' innate abilities.

A. Data

The examined sample is a panel data set providing micro-level information on worker performance. On an individual basis, it captures scanner transactions for build-up activities between October 2010 and August 2012. The time-variable of the panel is specified by one-hour-time intervals, t, and $T = 14,797$. A single observation provides information on how many shipment items a specific warehouse agent has contributed to a build-up unit during a one-hour-time interval. 175 warehouse agents are captured. Records for warehouse agents, who are observed in less than 30 periods, are excluded. Only periods are included during which at least two build-up agents were working simultaneously on one floor. Otherwise, peer effects can be ruled out. Entity-specific observations are only considered when they work in at least two subsequent time periods, t and $t+1$ (which is a result of using an estimation model in first differences). Transactions carried out for correction processes are excluded. Overall, the data set contains $39,446$ observations. The independent variable in all regressions is the logarithmic calculus of the number of build-up pieces of worker i in period t. The variable has been winsorized at the 1 percent level and 99 percent level. Table 1 provides descriptive statistics of the underlying sample. On average, a warehouse agent consolidates 25 shipment items per hour. Co-worker constellations change permanently. On average, six warehouse agents work simultaneously[30] (on one floor).

[30] That is, during a one-hour time period t.

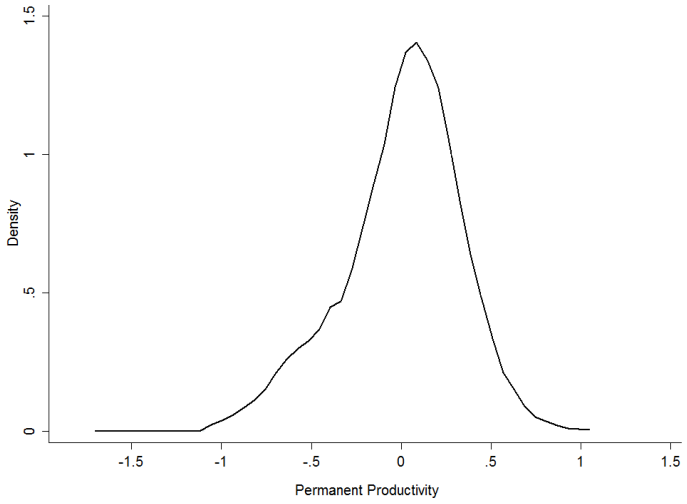

FIGURE 1: DISTRIBUTION OF WAREHOUSE AGENTS' PREDICTED PERMANENT PRODUCTIVITIES

Notes: Illustration of kernel density estimate of predicted worker-specific θ_i's (by fitting model 4), 175 warehouse agents are included, I use an Epanechnikov kernel with a bandwidth of 0.75.

B. Estimation of Permanent Productivity

According to the empirical procedure described in section III, peer effect estimation is performed in two steps. I begin by presenting the predicted θ_i's when estimating equation 4 (Step 1). For every warehouse agent i this fixed effects model predicts i's specific permanent productivity (individual deviation from panel mean). Recall, that the sampled warehouse agents perform the same task (consolidate shipment items onto build-up units with forklifts) and use the same technology for data capturing (barcode scanners with individual log-in). Moreover, they are provided similar incentives (fixed payment plus holiday premium and shift allowance). The set of estimated θ_i's represents the existent heterogeneity among the observed workers concerning their innate ability in the build-up procedure. Figure 1 illustrates the distribution of the estimated θ_i's. Analogue related studies, warehouse agents with a high θ_i are expected to be more productive than warehouse agents with a low θ_i. As illustrated by figure 1, there is substantial variation in individual innate ability, although I control for week-time patterns, number of present colleagues and co-worker constellations. Figure 2 plots the quantiles of the predicted θ_i's against the theoretic quantiles of a normal distribution (represented by the dashed diagonal). Because 175 warehouse agents are observed, I expected the predicted θ_i's to be distributed normally. The figure illustrates that the distribution of the predicted permanent productivities can be approximated adequately by a normal distribution.

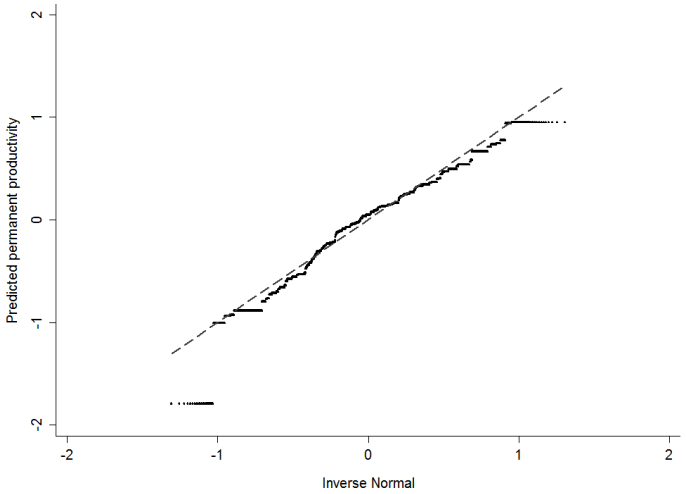

FIGURE 2: APPROXIMATION OF ESTIMATED θ_i'S BY A NORMAL DISTRIBUTION.

Notes: Plot of quantiles of predicted θ_i's (by fitting model 4) against theoretic quantiles of a normal distribution (represented by the dashed diagonal). 175 warehouse agents are included.

C. Estimation of Peer Effects

In the second step, the existence and the magnitude of compositional peer effects is estimated. Therefore, equation 7 is used. With the help of the predicted θ_i's, I calculate the average permanent co-worker productivity, $\bar{\theta}_{-it}$, for every warehouse agent i in every time period t. Recall, that $\bar{\theta}_{-it}$ is computed without using the permanent productivity of the focal warehouse agent i, θ_i.

The estimates of fitting model 7 to the data are presented by Table 2. Column 1 shows the baseline estimate of the parameter β. Since $\hat{\beta}$ is 0.159, a positive causal relation between changes in average permanent co-worker productivity and current output exists. The estimated coefficient suggests that a 10 percent increase (from period $t-1$ to t) in average co-worker permanent productivity is related to a 1.6 percent increase in current productivity of the focal worker. The estimated coefficient is statistically different from zero on a significance level of five percent (p-value is 0.031). In this setting, peer effects appear as productivity spillovers caused by social pressure.

To check the robustness of the estimation and to ensure that the predicted β is capturing the true compositional peer effect, I include further[31] control variables. First, I add a set of variables controlling for warehouse agent i's working tenure in days, warehouse agent i's number of shifts worked, warehouse agent i's sum of all consolidated build-up pieces during operational career as well as a dummy that is one if warehouse agent i is a shift supervisor and zero otherwise (Column 2). For the regression in Column 3, I additionally include controls for

[31] Note that the baseline estimation model 7 already controls for week time patterns, number of present colleagues and co-worker constellations (that is, for all observed compositions of build-up workers).

Table 2: Estimates of Compositional Peer Effects

	(1)	(2)	(3)
Δ average co-worker permanent productivity ($\hat{\beta}$)	0.159**	0.160**	0.146*
	[0.073]	[0.073]	[0.075]
Number of observations (N)	7,911	7,911	7,911
Controls for warehouse agent i		Yes	Yes
Controls for warehouse agent i's peers			Yes

Notes: OLS estimations of equation 7. Dependent variable: change of log in focal worker's current productivity between two consecutive time periods (symbolized by Δ), bootstrapped standard errors in parenthesis. Further information on the sample is listed in Table 1. Regression 2 includes controls for warehouse agent i's working tenure, i's number of shifts worked, i's sum of all consolidated build-up pieces as well as a dummy that is one if i is a shift supervisor and zero otherwise. Regression 3, additionally, controls for average working tenure, average number of shifts worked and average sum of all consolidated build-up pieces of warehouse agent i's peers (active in period t). $^{***}p \leq 0.01$; $^{**}p \leq 0.05$; $^{*}p \leq 0.1$.

warehouse agent i's colleagues who are active in period t. Specifically, I control for average working tenure, average number of shifts worked and average sum of consolidated build-up pieces of warehouse agent i's peers.[32] The estimate of β remains robust since predicted coefficients in Regressions (2) and (3) yield similar results with $\hat{\beta}$ being 0.160 and 0.146, respectively. Coefficients stay statistically significant (p-values are 0.031 and 0.055, respectively).

The underlying data contains two other measures for individual performance—the weight of all contributed build-up pieces by warehouse agent i over a one-hour time period t as well as the number of build-up scans[33] by warehouse agent i over a one-hour time period t. To verify the robustness of my results, I also use these performance measures as different dependent variables (y_{it}) to re-estimate equation 7 (and additionally include control variables).[34] As illustrated by table 3, results for estimated peer effects remain robust, invariably.

The presented estimates indicate the existence of positive compositional peer effects (occurring as productivity spillovers) caused by a change in average co-worker permanent productivity. When warehouse agents work together with more able peers, they are likely to put in more effort and improve their current performance. Reversely, free-riding can be ruled out in the examined working

[32] While controls included in Column 2 are worker-specific variables of the focal warehouse agent i (that is, controls are independent of period t), controls included in Column 3 are shift-specific variables which vary over t).

[33] The warehouse management IT system 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. Hence, warehouse agents are not forced to perform barcode scans of single pieces they build-up. Rather, they scan the shipment barcode and enter the number of related pieces with the help of the scanner keyboard to finalize the transaction.

[34] Note that – when using a different dependent variable – the individual permanent productivities, θ_i, also have to be re-estimated (by fitting equation 4 using the corresponding performance measure—that is, the weight of all contributed build-up pieces by warehouse agent i over a one-hour time period t or the number of build-up scans by warehouse agent i over a one-hour time period t, respectively.) Moreover, controls have to be adopted with regard to the used performance measure as described in the notes of table 3

Table 3: Estimates of Compositional Peer Effects using different Dependent Variables

	(1)	(2)	(3)	(4)	(5)	(6)
Dependent Variable	Σ BU Wgt	Σ BU Wgt	Σ BU Wgt	# BU Scans	# BU Scans	# BU Scans
Δ average co-worker permanent productivity ($\hat{\beta}$)	0.131**	0.133**	0.127**	0.150**	0.160**	0.146**
	[0.060]	[0.060]	[0.063]	[0.062]	[0.062]	[0.063]
Number of observations (N)	7,911	7,911	7,911	7,911	7,911	7,911
Controls for warehouse agent i		Yes	Yes		Yes	Yes
Controls for warehouse agent i's peers			Yes			Yes

Notes: OLS estimations of equation 7. Dependent variable: change of log in focal worker's current productivity between two consecutive time periods (symbolized by Δ). In columns 1 to 3, the original measure of productivity is the weight of all contributed build-up pieces by warehouse agent i over a one-hour time period t (abbreviated with "Σ BU Wgt"). In columns 4 to 6 the number of build-up scans by warehouse agent i over a one-hour time period t is used as measure for current productivity (abbreviated with "# BU Scans"). Bootstrapped standard errors in parenthesis. Regression 2 includes controls for warehouse agent i's working tenure, i's number of shifts worked, i's weight of all consolidated build-up pieces as well as a dummy that is one if i is a shift supervisor and zero otherwise. Regression 3, additionally to 2, controls for average working tenure, average number of shifts worked and average weight of all consolidated build-up pieces of warehouse agent i's peers (active in period t). Correspondingly, Regression 5 includes controls for warehouse agent i's working tenure, i's number of shifts worked, i's sum of all build-up scans as well as a dummy that is one if i is a shift supervisor and zero otherwise. Regression 6, additionally to 5, controls for average working tenure, average number of shifts worked and average number of all build-up scans of warehouse agent i's peers (active in period t). $^{***}p \leq 0.01$; $^{**}p \leq 0.05$; $^{*}p \leq 0.1$.

environment. In particular, I find that an increase in the average permanent co-worker productivity of 10 percent is associated with a boost in individuals' current performance of around 1.6 percent, on average. Interestingly, the magnitude of the peer effect estimate is similar to Falk and Ichino (2006) as well as Mas and Moretti (2009).

D. Heterogeneity

The baseline model 7 predicts one coefficient β for all subjects. That is, it assumes a constant peer effect magnitude across all warehouse agents. However, studies point out that the magnitude of peer effects may be a function of one's individual productivity level. For instance, Falk and Ichino (2006) and Mas and Moretti (2009) showed, that less productive workers are more likely to be affected by peer effects than high productivity workers.

To examine potential heterogeneity concerning the sensitivity to peer effects across warehouse agents with different levels of permanent productivity, I estimate the following model (Mas and Moretti, 2009):

$$\Delta y_{it} = \alpha + \beta \Delta \bar{\theta}_{-it} + \lambda \Delta \bar{\theta}_{-it} R_{iQ} + \Delta \gamma N_t + \delta_{dh} + \epsilon_{it} \tag{8}$$

Where R_{iQ} is a dummy that is one if the predicted permanent productivity of warehouse agent i, θ_i, is above a certain quantile boundary Q of the distribution of the θ_i's. In particular, I examine quartiles of the θ_i-distribution—that is, $Q_{0.25}$, $Q_{0.50}$ and $Q_{0.75}$ (representing 0.25-quantile, 0.50-quantile and 0.75-quantile), respectively. Thus, three regressions are performed to examine potential heterogeneity in responses across warehouse agents. The coefficients of interest are β and λ. $\hat{\beta}$ quantifies the reaction of a warehouse agent whose permanent productivity, θ_i, is below the corresponding quartile boundary Q ($\theta_i < \theta_Q$). The sum $\hat{\beta} + \hat{\lambda}$ represents the reaction of a warehouse agent whose permanent productivity, θ_i, is equal to or above the corresponding quartile boundary Q ($\theta_i \geq \theta_Q$).

Table 3 presents the estimates for β and λ of regression model 8 for different R_{iQ}-quartile dummies. None of the estimated coefficients for λ are statistically significant (Column 1 to 3). Hence, the data does not provide evidence for differences in peer-effect magnitudes across warehouse agents with different levels of permanent productivity.[35] This result is in contrast to expectations since in samples of related studies, also providing evidence on the existence of peer effects in the workplace, peer-effect magnitudes vary across examined individuals depending on their skill level (Ichino and Maggi, 2000; Falk and Ichino, 2006; Mas and Moretti, 2009).

To shed more light on agents' heterogeneity in responsiveness I estimate a random coefficient model where the β is allowed to vary by subject i. This approach is represented by the following equation (Mas and Moretti, 2009):

[35] Instead of using quartiles on the predicted θ_i-distribution, I also computed ranks of warehouse agents to perform this heterogeneity analysis. Results do not change, either—coefficients for λ remain insignificant. Results of the corresponding estimations are available on request.

Table 4: Heterogeneity of Peer Effect Magnitudes depending on a Warehouse Agent's Level of Permanent Productivity

	(1)	(2)	(3)
Δ average co-worker permanent productivity ($\hat{\beta}$)	0.131	0.196**	0.199***
	[0.370]	[0.044]	[0.012]
Δ average co-worker permanent productivity ($\hat{\lambda}$)	0.028	−0.082	−0.202
$\times$ above average agent ($R_{iQ} = 1$)	[0.874]	[0.588]	[0.320]
Number of observations (N)	7,911	7,911	7,911

Notes: OLS estimations of equation 8. Dependent variable: change of log in focal worker's current productivity between two consecutive time periods (symbolized by Δ), p-values in parenthesis, standard errors adopted with bootstrapping. Further information on the sample is listed in Table 1. In Column 1, $R_{iQ} = 1$, if θ_i is equal or above the rank of the first quartile of the distribution of the predicted θ_i's ($Q_{0.25}$), and zero otherwise. In Column 2, $R_{iQ} = 1$, if θ_i is equal or above the rank of the median ($Q_{0.50}$). In Column 3, $R_{iQ} = 1$, if θ_i is equal or above the rank of the third quartile ($Q_{0.75}$). $^{***}p \leq 0.01$; $^{**}p \leq 0.05$; $^{*}p \leq 0.1$.

$$\Delta y_{it} = \alpha + \beta_i \Delta \bar{\theta}_{-it} + \gamma \Delta N_t + \delta_{dh} + \epsilon_{it}, \tag{9}$$

where β_i represents a subject-specific peer-effect magnitude. Note that most estimates for $\hat{\beta}_i$ are not significant since individual-clustered sample size may not be large enough. Nevertheless, the results induce some further insights. Figure 3 plots the subject-specific estimates $\hat{\beta}_i$ against the levels of permanent productivity θ_i using a local-linear smoother analogue Mas and Moretti (2009). As shown graphically, there is substantial heterogeneity in peer-effect magnitudes across the observed warehouse agents, and magnitudes' variability seems to larger for low-skilled workers (both upturns and downturns). The β_i's of most agents are above zero (indicating a positive peer effect)—for some agents the effect is even large. Though, there are also agents with β_i being below zero (indicating a negative peer effect). These results seem not surprising. However, the graph neither reveals a causal nor a correlative relation between peer-effect magnitude and agent's permanent productivity θ_i. In the considered working environment the heterogeneity in responsiveness cannot be explained by an agent's innate ability. These results are consistent with my previous findings.

An explanation for the differential response to peer compositions could be that some warehouse agents are working at their potential, while others are not. For the latter, peer effects might have a relatively higher influence on performance because their potential for productivity enhancements might be more substantial. However, in contrast to the findings in Mas and Moretti (2009), it is not the case that only above average agents are working at their potential, while the below average agents are not. For the group of warehouse agents, something else is driving these differences in magnitudes. But, this is not explainable with the underlying data.

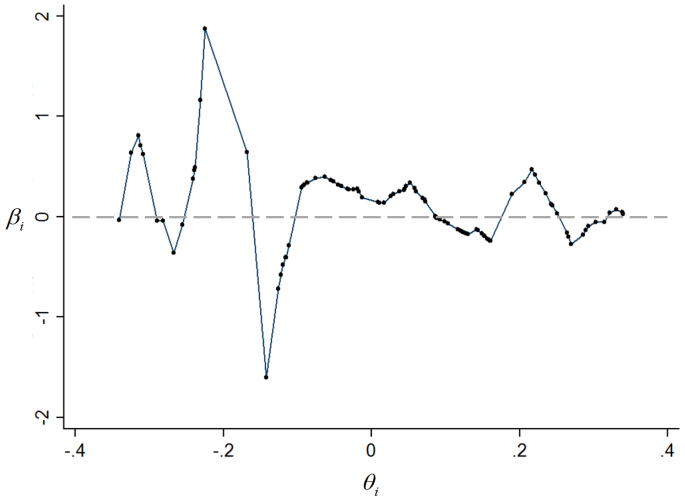

Figure 3: Relationship between Individual Permanent Productivity and Worker-specific Peer Effect

Notes: Plot of the local-linear regression fit for the relationship between the estimated worker specific peer effects β_i versus workers permanent productivity θ_i. Specification for figure presentation taken from Mas and Moretti (2009). Dashed lines are 95 percent confidence intervals. An Epanechikov kernel with a bandwidth of 0.02 is used, and the regression is weighted by inverse variance of the estimated worker-specific peer effects.

V. Conclusion

Although the list of academic papers on the topic of peer effects is long, there are only few field studies examining peer effects in a workplace environment. While some papers provide evidence on the existence of peer effects, others do not find significant results: Emergence and magnitude of potential peer effects in real workplace environments strongly depend on subjects, tasks and incentive schemes. For a better understanding of peer effect mechanisms in the workplace, further field studies in different organizational environments and on different personalities are necessary. The empirical study conducted within this paper contributes to the existing literature on this topic.

By using a large data set on performance of warehouse agents, I find evidence on the existence of positive compositional peer effects among observed subjects. These effects appear as productivity spillovers caused by social pressure. When co-workers' permanent productivity increases by 10 percent, the current performance of a focal warehouse agent is raised by 1.6 percent, on average. Hence, systematic free riding can be ruled out. Moreover, the data provides evidence for differences in peer-effect magnitudes across considered warehouse agents. In contrast to related studies, these differences in responsiveness cannot be explained by different levels of permanent productivity.

In general, the existence of peer effects within this freight handling process imply that the overall return of hiring an above average warehouse agent is

higher than his individual output contribution. Hence, in freight business firms can exploit social incentives as an alternative to monetary incentives to fill the gap of incomplete working contracts and motivate workers. Additionally, shift compositions can be optimized to maximize output in the long run. The results of this paper are a complement to existing studies on this topic.

Appendix

Place Figures Here.

Table 5: Number of Warehouse Agents simultaneously working on a single Build-Up Unit.

No. of Agents	Frequency	Percent	Cumulative
1	72,217	86.91	86.91
2	9,108	10.96	97.87
3	1,542	1.86	99.73
4	184	0.22	99.95
5	40	0.05	100.00
Total	83,091	100.00	100.00

Table 6: Frequencies of specifc Team Constellations of Warehouse Agents working on a single Build-Up Unit.

No. Obs.	Frequency	Percent	Cumulative
1	3,897	35.84	35.84
2	1,418	13.04	48.88
3	1,014	9.32	58.20
4	588	5.41	63.61
5	540	4.97	68.58
6	486	4.47	73.05
7	301	2.77	75.81
8	256	2.35	78.17
9	270	2.48	80.65
10	230	2.12	82.77
11	176	1.62	84.38
12	168	1.54	85.93
13	156	1.43	87.36
14	84	0.77	88.14
15	150	1.38	89.52
16	64	0.59	90.10
17	68	0.63	90.73
18	144	1.32	92.05
19	76	0.70	92.75
20	40	0.37	93.12
23	92	0.85	93.97
25	50	0.46	94.43
26	52	0.48	94.91
27	108	0.99	95.90
29	58	0.53	96.43
31	124	1.14	97.57
34	68	0.63	98.20
48	96	0.88	99.08
50	100	0.92	100.00
Total	10,874	100.00	100.00

Notes: In $10,874$ out of $83,091$ single build-ups, more than one warehouse agent works on one and the same build-up unit. For these cases, this table illustrates frequencies in observations for identic team constellations of workers simultaneously proceeding on one and the same build-up unit. The table shows, for example, that there are 230 observed cases (out of $83,091$) that a specific team-constellation worked together.

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