The Value of a Peer*

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Abstract

This paper introduces a new approach to peer effects: Peer value-added isolates the total contribution of an individual to the performance of others without relying on observable peer characteristics as measures of peer quality. Using data from a setting with repeated random assignment of students to peer groups we show that there is significant variation in peers' value-added. Peer observable characteristics, most notably previous performance, are poor predictors of individual spillovers. We validate our peer value-added measures in out-of-sample social interactions and show that peer value-added captures performance and earnings spillovers among randomly re-assigned peers. We establish that the ability to raise others' performance is a malleable trait. Students interacting with peers generating positive spillovers become more valuable peers themselves.

Keywords: peer effects, social capital, peer value-added, spillovers
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1. Introduction

Social interactions are a major source of learning. In education and the workplace, we learn from each other and become more productive if we meet the right peers. But who are the peers that bring out the best in us? The quest to identify valuable peers has motivated a large literature on how observable peer characteristics affect individual performance. After decades of research, however, researchers have not reached a consensus on the size of peer effects, which peer characteristics generate spillovers, and how to estimate peer effects (Sacerdote, 2014).

This paper introduces a new concept to quantify the importance of peers. We isolate the value-added of an individual peer to others' performance – the *peer value-added*. Peer value-added summarizes any source of spill-over on others' performance, e.g. supportive or disruptive behavior, degrees of complementary in skill sets, or differences in non-cognitive skills contributing to a productive learning environment.

Individual level measures of a peers' value-added can be estimated in any setting of repeated observations with changing peer composition. We estimate peer value-added in a sample of students from a Dutch University where students are repeatedly and randomly assigned to sections of 10-15 peers. Our results indicate significant variation in peer value-added which cannot be explained by observable characteristics. We validate peer value-added as a good predictor of spillovers among newly assigned peer groups. We show that peer value-added changes over time, which can be partly explained by exposure to high value-added peers in previous periods.

To estimate peer value-added, we follow four simple steps. First, we reshape the data into a dyadic dataset where each one-to-one interaction between a student and a peer represents one observation. Second, we compute performance residuals adjusting for the level of randomization to isolate exogenous variation due to changes in peer composition. Third, we obtain peer value-added by averaging residual performance of those students who meet a respective peer in their studies. Fourth, we apply a Bayesian shrinkage estimator to these peer value-added measures to increase their predictive power.

We estimate students' peer value-added with this method and document three sets of results. First, peers differ significantly in their ability to raise their fellow students' performance. A one standard deviation increase in peer value-added raises fellow students' current grades by 3.3 percent of a standard deviation. The majority of peers, however, has only small impacts on performance: Out of all peers that students interact with, only 14 percent affect grades by more than 5 percent of standard deviation. Who are these peers? When looking at what makes a good peer we find that peer value-added is only very weakly correlated with the lagged achievement of a peer. Further peer characteristics do not predict peer value-added in a systematic way. In contrast to the econometrician, though, fellow students seem to notice valuable peers and report improved peer-to-peer interactions in their course evaluations when high value-added peers are present.

Second, we find that peer value-added is systematically correlated across outcomes, subjects, and time and is a valid predictor for spillovers in newly assigned – *out-of-sample* – social interactions. We find that the same peers that raise todays' performance on average also increase subsequent performance and graduation probabilities. When estimating PVA separately for math-intensive and non-math intensive courses we find that peer value-added is correlated across these contexts. We find suggestive evidence that interacting with valuable peers has persistent effects on labor market outcomes: students exposed to high value-added peers report higher earnings 1-2 year after graduation.

Third, we show that changes in peer value-added over time can partly be attributed to social interactions with other valuable peers. Students who were randomly assigned to peers with a high

PVA in the first study year have a significantly higher own PVA in subsequent periods. These learning effects imply that students who meet high value-added peers do not only perform better themselves, but subsequently also produce larger spillovers on others – they become better at teaching other students.

Our study relates to the extensive literature on exogenous peer effects that studies externalities arising from the peer composition on own performance or behavior. In general, these *canonical* peer effect studies relate a group-level aggregate of a single observable characteristic to individual outcomes. Linear-in-means and linear-in-shares models study, for example, how student test scores are affected by peer achievement, the share of black, female or free-lunch peers.[1] These models, in contrast to our framework, are motivated by the idea that the ability of raising others' performance is closely related to own observable characteristics.

With this paper, we make a number of conceptual and empirical contributions. Conceptually, our approach to model peer effects to arise from individuals' peer value-added is different from the current state of the art in the literature which approximates peer effects as a function of group characteristics. By recognizing that spillovers can arise from both observed and *unobserved* peer characteristics we propose a more comprehensive view on peer effects that can go beyond observables like gender, race or achievement. By taking the concept of peer value-added to the data, we contribute to a more nuanced understanding of peer effects in education. The lack of correlation between peer value-added and observable peer characteristics demonstrates that observables do not always correlate with social spillovers. By providing empirical evidence on the

[1] Epple and Romano (2011) and Sacerdote (2011) provide comprehensive literature overviews on the peer effects literature. Booij, Leuven and Oosterbeek (2017), Carrell, Sacerdote and West (2013) as well as Garlick (2018) provide more recent evidence on ability peer effects.

generalizability, stability and malleability of peer value-added we take the first steps to understand the intrinsic meaning of peer-added and what environmental factors shape it.

Our approach to identify peer value-added is inspired by the literature on teacher effectiveness.[2] Similar to findings in the teacher value-added literature, we find that observable characteristics are not very good predictors for spillovers. Comparing teachers to peers shows that variation in teacher value-added is 3-5 times larger than variation in peer value-added – a single peer is far less important as a single teacher. Peer value-added is also less stable over time with a year-to-year correlation of about .1 compared to .2 - .7 for teachers. We show that part of the transitory component of peer value-added can be explained by exposure to high value-added peers in earlier periods.[3]

Finally, our study also relates to several strands of the literature studying the influence of bosses and co-workers. To the literature on complementarities and learning among co-workers (Park 2019, Jaravel et al 2018, Jarosch et al. 2018, Mas and Moretti 2009, and Cornelissen et al. 2017) we add the perspective of comprehensive spill-overs by both observable and unobservable factors. To the literature on the effectiveness of bosses (e.g. Lazaer et al. 2012) we add a perspective of *horizontal* spillovers among co-workers.[4] Our findings raise an interesting question with respect this literature and the complementarities among workers in the workplace: Do firms pay high peer value-added workers higher wages? Firms who ignore the peer value-added of their workers and

[2] Koedel et al. (2015) and Hanushek & Rivkin (2006) provide a comprehensive review on the extensive literature on teacher value-added. When estimating peer value-added we draw on insights from Kane & Staiger (2008), Chetty et al. (2014a, 2014b) to avoid bias and to obtain the best linear predictors of value-added.

[3] Jackson & Bruegmann (2009) present similar results for teachers and show that teacher value-added is affected by the value-added of fellow colleagues.

[4] The only study we are aware of that similarly identifies comprehensive and single peer-specific spillovers, albeit tampered by data constrains and therefore relying on strong structural assumptions, is Arcidiacono et al. (2017) who use possession-player level data from the National Basketball Association to estimate player-level contributions to others' performance. We discuss their approach in Section 6.

only pay their employees based on their own productivity may dis-incentivize workers who bring out the best in others.

Identifying single peer-specific spill-overs is relevant for many applications in education and labor economics. Whenever students and workers are to be incentivized, evaluated or paid according to their marginal productivity we want to know what spillovers they create. Although peer value-added can only be estimated *ex post*, there is increasing scope for applications in settings with contemporaneous monitoring of performance, e.g. in settings of real-time monitoring of performance through data warehouses in manufacturing. In such cases, worker peer value-added could be estimated in initial test periods and subsequently used for optimal team re-assignment. Attempts to re-assign students based on canonical peer effect estimates have not been successful in the past (Carrell et al., 2013). We believe that knowledge of peer value-added, the individual-specific spillover, is important for allocating individuals to output maximizing teams.

The remainder of the paper is structured as follows. In section 2 we lay out the conceptual framework of peer value-added. In section 3 we describe the institutional details and data we use, Section 4 describes the estimation steps of PVA. In Section 5 we present results on the magnitude, heterogeneity and malleability of PVA and validate PVA as a predictive factor for peer performance across time and context. Section 6 discusses the findings in lieu of the existing literature and their potential applications. Section 7 concludes.

2. Conceptual Framework

In this paper, we quantify the contribution that individual peers have to the performance of surrounding students. In our framework some peers raise others' performance, others lower it. We label the effect of a peer on surrounding students their peer value-added (PVA). In the following, we describe how the peer value-added perspective differs from standard peer effect models, how to incorporate PVA in a formal education production framework, and what kind of variation is captured by PVA.

The peer value-added approach we propose in this paper differs in two important ways from what we label canonical peer effects studies. First, PVA identifies the *single peer-specific* contribution to performance. Specifically, PVA describes the expected performance change from meeting that peer relative to meeting a peer with average value-added. The canonical peer effect approach, in contrast, focuses on the contribution of an entire *group of peers*. The contribution of this group is then approximated by peer averages of test scores or the share of female, black, or free-lunch receiving peers. By describing individual outcomes as a function of such observable group characteristics canonical studies are by design not capable of singling out contributions of single peers.

Second, PVA captures the *overall contribution* to others' performance instead of focusing on spill-overs of single observable dimensions like lagged achievement, gender or ethnicity. This distinction is especially important when peer effects are driven by non-cognitive skills or behavioral differences which are often not observed by the researcher. When unobserved peer characteristics create spillovers, canonical peer effects study only identify these spill-overs if the respective unobservable factors are sufficiently correlated with observables. Therefore, canonical peer effects studies might falsely conclude that peer effects are small or non-existent when observable characteristics do not sufficiently capture spillovers.

How does peer value-added enter the simple educational production function? The content of PVA can be described in a simple educational production function framework where student *i* is assigned to peers in peer group *s*:

$$y_{is} = \alpha_i + \delta_s + \epsilon_{is}. \tag{1}$$

In equation (1) y_{is} represents the outcome, e.g. performance, of student *i* in peer group *s* which is assumed to be an additive function of individual factors α_i, factors associated to the peer group environment (δ_s) and idiosyncratic individual-peer group specific shocks ϵ_{is}.

The peer group environment of a student contains all influences that are related to the composition of a specific peer group. In addition, it contains factors that are affecting individual outcomes simultaneously to the peer composition, e.g. classroom and teacher quality. These latter factors are often subsumed under the label of common shocks in peer effect studies. The peer environment δ_s therefore can be decomposed into

$$\delta_s = f(\omega_j, j \in s_{-i}) + \mu_s. \tag{2}$$

The term $f(\omega_j, j \in s_{-i})$ describes a function of a specific peer group composition *j*, disaggregated into single-peer specific components ω_j. These single ω_j represent the peer-specific value-added that we seek to identify with our approach, i.e. the PVA of a single peer $j \in s_{-i}$. This notation expresses that a student does not influence herself as a peer. The remaining common shocks unrelated to peer composition are denoted by μ_s and have to be separated from peer spillovers in any attempt to estimate ω_j.

The single peer-specific and comprehensive contributions ω_j capture any variation in outcome y_{is} that can be attributed to a specific peer j. Variation in single peer-specific value-added can arise from differences in peer behavior, skills, abilities or traits, which are often difficult to observe in the field. We can draw insights about what is captured by peer value-added from the field of organizational psychology which has a long-standing tradition analyzing individual traits which maximize team performance. Pro-social peers might deliberately support other students (Brief & Motowidlo 1986). Some valuable peers have skill sets that are complementary to other students' learning progress (Katzenbach & Smith 2015). Others might act as role models inspiring effort provision in their fellow students. Further, students might possess specific personality sets that generate a productive learning environment for their fellow students (Barrick et al. 1998). Of course, these mechanisms can be negatively framed, too: students can be disruptive, possess a non-complementary skill set, discourage students from providing effort and generate a hostile environment through their personality. Whatever a peers' exact contribution is, will be captured by ω_j.

The ability to raise others' performance might depend to some degree on the specific peer composition, curriculum or teacher in a classroom. Therefore, PVA might consist of a fixed and a transitory component that might display complementarities of peer spill-overs with certain teaching-styles, curricula or other peers' behavior:

$$\omega_{js} = \omega_j^* + \nu_{js} \tag{3}$$

Here, ω_j^* describes the context-independent value-added of a specific peer on others' performance that is stable throughout a period. The transitory component ν_{js} instead varies with contextual effects, e.g. the specific peer composition s_{-j}, and teacher or course effects.

The context-independent, non-transitory component of PVA ω_j^* may change over time, too. Students might adopt beneficial behavior of peers they observed in earlier peer groups. Newly acquired skills might differ in their complementarity to others' skills. Individuals might reflect about discouraging and disruptive behavior and copy or interrupt it in the future. Though we will later assume that PVA is to some degree stable within periods, we will also relax this assumption to account for potential systematic longer-term changes in peer value-added.

3. Data, Institutional Environment and Randomization

To estimate peer value-added in a field setting with meaningful social interaction, we use data from a Dutch business school where students are repeatedly and randomly assigned to study sections. In this section, we provide an overview of the institutional details, introduce the dataset and demonstrate the actual randomness of the assignment process. A more detailed description of institutional details can be found in the appendix.[5]

3.1 Institutional Environment

The data we use stems from a Dutch business school that offers bachelors, masters, and PhD programs in Economics and Business. Our analysis focuses on the two largest study programs in

[5] A similar description of the institutional details is provided in Elsner, Isphording and Zölitz (2018) as well as Feld and Zölitz (2017).

which all first-year bachelor students follow the same general course structure and the same set of compulsory courses. Teaching at the business school takes place in four regular teaching periods per academic year, with each teaching period lasting about two months. Students sit centrally graded written exams at the end of each period. In the first year of study course grades are identical to exam grades. Starting from the second-year course grades have a participation component that contributes up to 20 percent of the final courses grade.

The business school's teaching concept focusses on group work. While students attend lectures once or twice per week, section meetings are a major component of their studies. These two-hour-long sessions usually take place twice per week. Students typically work on their study material alone or in groups and then come together to discuss the material with their section peers. The instructor, who can be a professor, lecturer, or graduate or undergraduate student, monitors and, if necessary, directs the discussion.

A key feature of the business school is that, within each course, the scheduling office randomly assigns students and teachers to sections of up to sixteen students. The random assignment is a byproduct of the scheduling software used at the institution. Students or instructors do not interfere with this process. Since 2011 assignment is stratified by nationality to avoid that there are, by chance, "too many" German or Dutch students are assigned to one section. Some courses are also stratified by exchange student status to avoid that, by chance, too many exchange students are allocated to one section. After students are assigned, schedulers manually re-assign students with scheduling conflicts to other sections, which occurs for about 5 percent of the sample.[6] We exclude a few cases from the analysis, where course coordinators did not comply with the standard allocation procedure.

The assignment of students to sections is binding. Switching from the assigned section to another is allowed only for medical reasons or when the student is a top athlete and must attend sports practice. Students are required to attend their designated section. To be admitted to the exam, they must not miss more than three meetings of their designated section. Instructors keep a record of attendance. The attendance data are not centrally stored and thus are not available to us.

3.2 Data

Panel A of Table 1 provides basic descriptive statistics of the original data. We observe 4,729 students in 6 subsequent cohorts. Female students make up 37 percent of the sample. The average student is 19 years old. Only 29 percent of the studentship is of Dutch nationality, while 36 percent are of German nationality.

On average, we observe students in 14.3 sections during their compulsory stage, in 6.2 sections in the first and in 8.1 sections in the second and third year. Through these section assignments, they meet on average 55 different peers in the first and 86 in the second and third year.

Educational Outcome Variables – Students Grades and Graduation: At the end of each teaching period, students must sit an exam which results in a final course grade. In the first-year

[6] To test if this conditioning of the random assignment affects results, we included parallel course fixed in the estimation as one of our robustness checks. These fixed effects did not have any meaningful impact on our results.

courses we study, these grades are exclusively based on centrally graded, final exam performance. The business school uses the Dutch grading scale which ranges from 1 to 10, with 5.5 being the lowest passing grade. To simplify the interpretation of our estimates we standardize grades to mean zero and standard deviation one over the estimation sample. We further generate indicators for course passing and graduation. In the analysis of graduation probabilities we restrict our sample to students who could have graduated by the end of our observation period given their enrolment year.

Survey Outcomes Variables – Student Course Evaluations: To explore mechanism that drive any effects on academic and labor market outcomes, we use students' individual level responses to the course evaluation survey that take place at the end of each course. The course evaluation survey is sent out at the end of each course but before students take the final exam. Responses to student evaluations are non-compulsory, and response rates are at about 35 percent. From the course evaluation survey, we obtain three variables of interest: 1) self-reported study hours per week, excluding contact hours; 2) subjective overall course quality on a ten-point scale, with 10 being very good; 3) and a quality of peer interaction index as the average of the standardized value of the two evaluation items: "My tutorial group has functioned well."; "My fellow-students helped me to better understand the subject matter". We standardized the quality of peer interaction index to have a mean of zero and a standard deviation of one over the estimation sample.

Student Earnings: To gather data on students' earnings, we conducted a graduate survey in 2016 among students who graduated between September 2010 and September 2015 which provides us with information on yearly earnings in Euro before tax. In our analysis we focus on students earnings reported in this survey. Earnings are only available for students that took part in the graduate survey – 35% of the estimation sample. Student response is unrelated to our measures of peer value-added and inverse probability weighting of earnings leads to qualitatively similar results.

3.3 Randomization Check

A necessary identifying assumption of our approach is that students are randomly allocated to groups. To test this assumption in the most direct way possible we regress student `pre-treatment' characteristics (previous GPA, age, gender and the rank of the student ID) on group dummies that refer to the assigned tutorial group in which we observe students. This test is proposed by Wang (2010) and recently used by Cullen et al. (2019) as a method to detect ability tracking within schools. Under random assignment we would not expect group dummies to jointly predict pre-treatment characteristics. Under random assignment we would further expect the F-test to be significant at the 5 percent level in approximately 5 percent of the cases, at the 1 percent level in approximately 1 percent of the cases, and at the 0.1 percent level in approximately 0.1 percent of the cases. Table 2 provides summary statistics for these balancing tests and shows that the actual rejection rates are close to the rejection rates expected under random assignment. Further, F-tests for joint significance of the section dummies show that the p-values of these F-tests for all courses in our sample have the properties that we would expect under random assignment: p-values are uniformly distributed with a mean close to 0.5.

4. Estimation of Peer Value-added

4.1 Overview

In order to obtain a separate peer value-added estimate for each student, our empirical strategy has (1) to separate single contributions from common shocks, i.e. instructor and classroom influences, and (2) has to separate single peer contributions from one another. Intuitively, we achieve this goal by relying on the random assignment of peers to learning groups (sections) to compare the average performance of all students who met peer j with the average performance of the group students who met student $k \neq j$. We start by briefly outlining the four core steps of this estimation which is inspired by methods developed by Chetty et al. (2014a) to estimate teacher effectiveness. Below we explain each step in greater detail and discuss the necessary assumptions underlying the estimation.

In the first step of estimation we reshape the data that originally comes at the individual $\times$ section level into a *dyadic* dataset on the individual $\times$ peer $\times$ section level where each student-peer match represents one observation. This step represents the key difference to the canonical estimation of peer effects and allows us to estimate spillovers from many one-to-one interactions to single out individual-specific value-added.

In the second step we isolate that variation that can be credibly attributed to exogenous changes in peer composition. To do so, we estimate residuals from a regression of performance on fixed effects that account for the level of any non-exogenous sorting patterns, i.e. course × term fixed effects representing the level of randomization of students into sections. The resulting residuals separates arguably random variation in peers from variation that would potentially have been affected by selection of students into courses.

In the third step we create peer level average residuals of all student-to-student interactions with the same peer. This step identifies a peers' average contribution to the performance of all those students she met as their peers. This average is the *raw peer value-added*.

Finally, in the fourth step we increase the predictive power of these raw value-added measures by applying a Bayes estimator that shrinks PVA towards zero by assigning smaller weights to peers who are characterized by a higher variance in the residual performance of students they meet. These shrunk peer value-added estimates are the final PVA measures we refer to throughout this paper. The shrinkage procedure is inspired by the work of Jacob and Lefgren (2005) and Chetty et al. (2014a; 2014b). Shrinking peer value-added greatly increases the predictive power of our estimates for out-of-sample predictions.

In the following sections we describe these four core steps to obtain peer value-added in greater detail.

4.1 Reshaping the Dataset

In our data, we observe individual student i taking course c and being randomly assigned to a section s (the peer group) nested in the course. The single peer-specific value-added to others' performance is not identified in this conventional data setup organized on the individual × section level. To estimate single PVA, we have to observe a single peer in a multitude of different interactions with different individuals. We therefore reshape the original student-section level data into dyadic data at the level of student × peer interactions. Each student-peer pair that meets through assignment to sections constitutes a single observation.

Formally, we reshape the data on the $i \times c \times s$ level into dyadic data on the $i \times j \times c \times s$ level where $j = 1, \ldots, J \in s_{-i}$, i.e. where j denotes all peers being assigned to a tutorial while a student is not assigned to himself. The reshaping of the data increases the number of observations from $\sum_{c=1}^{C} \sum_{s=1}^{S} n_{cs}$ to $\sum_{c=1}^{C} \sum_{s=1}^{S} n_{cs} \, (n_{cs} - 1)$ observations.

The composition of these sections within a given course is entirely due to the random assignment to sections. Focusing on all students in a section sections as potentially relevant peer implies a first assumption about who we allow to generate spillovers:

Assumption 1 [Relevant peers]: For each student i, each peer j with $i, j \in s$ is a relevant peer.

This assumption specifically excludes cases of further ability segregation or endogenous peer selection within sections, i.e. that well-performing students only interact among each other.[7]

Under this assumption, we can estimate performance spillovers at the level of a single *peer* from many one-to-one interactions instead of modelling spillovers as functions of characteristics of peer *groups*. Table A1 in the appendix provides a simple illustrative example of the data before and after reshaping. In this example we observe 5 individuals who are attending two sections A and B, each containing 3 peers. Panel A shows the data structure before reshaping. We now observe Julian, Dick and Anne in Tutorial A, and Anne, George and Timmy in Tutorial B. We hence observe Anne in both tutorials. The number of observations is $\sum_{c=1}^{C} \sum_{s=1}^{S} n_{cs} = 6$. We now reshape the data to the student-to-student interaction level, so that each student pair that meets constitutes a single observation. We observe Julian, Dick, George and Timmy in one section each, hence

[7] In Section 5.3 we study how student-peer match characteristics matter for PVA and provide empirical support for this assumption.

interacting with two peers respectively. Anne, though, we observe in four social interactions, with 2 peers in 2 sections each. The number of observations in this reshaped data is now $\sum_{c=1}^{C}\sum_{s=1}^{S} n_{cs}\,(n_{cs}-1)=12.$[8]

4.2 Predicting Residuals

We isolate the variation that is induced by the randomized assignment to tutorials by predicting residuals from a regression of performance on fixed effects for the level of randomization. This step separates the arguably exogenous variation in peers' value-added to performance plus other unobserved factors varying idiosyncratically at the individual × section level from variation that is potentially induced by selection into courses. We accordingly estimate the regression

$$y_{ijcs} \;=\; \gamma_c + \varepsilon_{ijcs} \tag{4}$$

and obtain residuals as

$$y^{*}_{ijs} = y_{ijcs} - \hat{\gamma}_c \tag{5}$$

[8] Table A1 provides key numbers of the reshaping process. In the initial data, we observe 4,729 distinct students (and hence peers) who meet in 2,567 sections in 176 courses (the level of randomization). In our reshaped dataset we then observe 289,919 student-to-student interactions. On average, each student meets 55 unique peers during the first year in on average 6 different teaching sections.

where $\gamma_c$is a fixed effect for the level of randomization , the course-times-year level. Note that we dropped the now obsolete subscript c after residualizing to within course variation.[9]

4.3 Aggregating to Peer Value-Added

We separate single peer-specific spillovers ω_j by averaging across all dyadic observations including peer j. In order to identify the single peers' contribution ω_j in this way, we impose the assumption that single peer spill-overs affect individual performance in an additive way:

Assumption 2 [Functional form]: Peers j influence student i's performance through an additive function of single peer spill-overs, $f\left(\omega_j, j \in s_{-i}\right) = \sum_{j \in s_{-i}} \omega_j$.

To formally demonstrate how we achieve the identification of single ω_j, we first adapt the educational production function to the dyadic setting as

$$y^*_{ijs} = \omega_j + \delta_s + \varepsilon_{is} \quad \text{with} \quad \delta_s = \sum_{k \in s_{-i,j}} \omega_k + \mu_s \tag{6}$$

In equation (5), outcome y^*_{ijs} of individual i meeting peer j in section s is a function of j's spill-over ω_j and the remaining factors on the group level δ_s These remaining group level factors include peer spill-overs of all peers in the group other than j as well as common shocks on the group level.

[9] In practice, we further control at this step for individual pre-determined characteristics (gender, age, nationality) and teacher fixed effects to increase the efficiency of our estimates. This step is not necessary for identification and omitting these controls does not change the pattern of our results. We omit the characteristics for the sake of clarity of exposition.

Averaging the residuals y^*_{ijs} at the level of a specific peer j leads to:

$$\text{Raw PVA}_j \; = \; \overline{y^*_{ijs}} = \omega_j + \vartheta_{is} \;\; with\, \vartheta_{is} = \overline{\alpha_i} + \overline{\delta_s} + \overline{\varepsilon_{is}} \qquad (7)$$

Hence, our raw measures of PVA at the individual peer level consist of the individual contribution to others' performance ω_j plus a noise factor induced by the randomization process. This noise consists of the average of common shocks δ_s of those groups a peer j was randomly assigned to, the average of individual fixed component α_i of individuals he/she met through the random assignment, and the average of idiosyncratic shocks on the individual-section level ε_{is}. By definition, individual effects α_i, peer spill-overs ω_j and common shocks on the section level δ_s are defined as deviations from the average, so that $E[\alpha_i] = 0, E[\omega_j] = 0$ and $E[\delta_s] = 0$. The randomization of students to peer groups, and hence to peers, ensures that the individual component and peer spillover will be orthogonal so that $E[\alpha_i\, \omega_j] = 0$. It further ensures that a single peers' contribution to others' performance is unrelated to the peer spillovers of the remaining students assigned to a tutorial, E[$\omega_{is}\omega_{js}$]= 0. Finally, the randomization ensures that common shocks at the section level are orthogonal to a peers' contribution, so that $E[\omega_j\delta_s]$= 0. Then, within all student-to-student interactions with a given peer j, ω_j is independent from individual effects and common shocks which will be zero in expectation. As such, averaging over all interactions with peer j, will result in an estimate for ω_j, the individual-specific value-added.

Our conceptual framework in Section 2 allows single peers' spillovers ω_j to consist of a context-independent and time-invariant component ω^*_j and a transitory component ν_{js} that potentially varies with the specific peer composition (i.e. further peers' spillovers $\omega^*_{k\neq j}$ or classroom and teacher effects subsumed in δ_s). As described above, δ_s is orthogonal to single ω_j, so that such interaction effects do not impede identification. We do assume, though, that transitory components do not change systematically within periods and across contexts:

Assumption 3 [Stationarity and time invariance]: Changes across contexts (sections) in transitory components of peer spill-overs ν_{js} follow a stationary process. Context-independent components ω_j^* are constant *within* but may change *between* periods.

Assumption 3 does not rule out over-time changes and malleability in PVA per se. Such changes in the non-transitory component ω_j^* should manifest over longer periods (in our case between teaching years), while they are assumed to be invariant *within* periods.

4.4 Shrinking Estimates

Our raw estimates of PVA consist of a peers' contribution and a random error term resulting from random assignment to sections. To increase the predictive power of the PVA measures – in light of potentially considerable noise – the fourth and final step in the construction of peer value-added is to multiply the raw the raw measures of peer value-added with an estimate of their reliability. Intuitively, by using this procedure, we reweight peers by their within-peer variance of outcomes across the peers the student meets. In general, this higher variance coincides with a lower number of peer observations. Jacob and Lefgren (2005) show that using empirical Bayes estimates as the explanatory variable in a regression yields point estimates that are unaffected by the attenuation bias that would result from using standard OLS estimates.

This Bayes estimator of peer value-added shrinks PVA towards the sample mean and assigns less weight to peers who have a higher within-peer variance in PVA:

$$\mathrm{PVA}_j \;=\; \mathrm{Raw\;PVA}_j * \frac{\sigma^2}{\sigma^2 + \sigma_t^2} \tag{7}$$

Here, σ^2 is the sample variance $\sigma^2 = \frac{1}{n}\sum RawPVA^2$. The σ_t^2 displays the within-peer variance of residuals across time obtained from student-to-student interactions of peer j, $\sigma_t^2 = \frac{1}{n}\sum RawPVA_j^2 \mid i, j \in s$. Intuitively, peers' PVA that is more volatile over time will be measured with a lower signal-to-noise ratio and will receive a lower weight during estimations.

The resulting final peer value-added estimates PVA_j are the measures we use throughout the remainder of this paper. Empirically, raw PVA and final PVA have a correlation of .81. The shrunk estimates are the best linear unbiased predictor of a peers' impact on others performance, a result established in the teacher value-added literature (Kane and Staiger, 2008, p.2).

4.5 Peer value-added and common shocks

It is noteworthy that spillovers as expressed by a peers' PVA are robust against the problem of common shocks which complicates identification in conventional peer effect studies. As we observe single individuals in different, randomly assigned groups, common shocks, i.e. any kind of unobserved influence that comes with the assignment of peers, will be uncorrelated across groups in which a given peer is observed. We therefore can separate the influence of peers from these idiosyncratic influences which are part of the groups-specific environment μ_s and do not systematically vary with PVA. The intuition is that, since many different interactions in many different classrooms contribute to PVA estimates, we would not expect common shocks to occur in all those groups where a specific peer is present.

4.6 Peer Value-Added and the Reflection Problem

The reflection problem – called the simultaneous equations problem outside the hothouse of the peer effects literature – describes that explaining an individuals' outcomes using peer averages of the same outcomes is not necessarily informative of social spillovers. When testing if peers contemporaneous test scores affect own contemporaneous test scores it is thus not possible to disentangle whether group behavior affects individual behavior or if group behavior is simply the sum of individuals' behaviors. To circumvent this problem the canonical peer effects literature has converged to using pre-treatment leave-out-mean characteristics of peers.

Does the reflection problem affect the peer-value added measures that we estimate? This is not the case. Since our empirical approach does not rely on regressing individual outcomes on peer outcomes we do not face a simultaneous equations problem. Peer value-added measures are constructed by averaging residual grades over peers. Neither peer grades nor peer residual grades do at any point enter the estimation of peer value-added. The peer value-added that we assign to a peer does therefore not include any component related to own contemporaneous performance which would induce a simultaneous equation problem.

5. Results

We now present of our estimates of peer value-added from the setting of a Dutch Business school. We present results in two parts. We start by describing the variation in PVA in our sample in Section 5.1. Here, we examine how much peer value-added differs between students and whether differences in PVA can be explained by observable student characteristics. We further examine pairwise correlations between PVA for different outcomes, e.g. whether the same peers that raise grades also raise students' graduation probabilities.

In Section 5.2 we validate our estimates as meaningful measures of peer value-added. We first analyze the stability of PVA across different subjects and over time. We then show that that PVA has predictive power for out-of-sample social interactions. We further show that part of the transitory component of PVA can be explained by exogenous exposure to different peers itself. Finally, we examine whether peer value-added interacts with characteristics of specific student-peer matches in Section 5.3.

5.1 The Variation in Peer Value-Added

We use the method outlined in Section 3 to construct peer value-added for a number of objective and self-reported outcomes. Objective outcomes include performance measures: grades in the first study year, average grades in the second and third year, and an indicator of graduation.[10] Self-reported measures are based on student answers to teaching evaluations and include self-reported study hours and assessments of the quality of peer-to-peer interactions.

Variation in peer value-added. Figure 1 shows distributions of individual level peer-value-added for performance and graduation. The figure visualizes how much heterogeneity between in single peers contribution to these outcomes we observe in the data. PVA is almost symmetrically distributed around zero for both grade-based outcomes and graduation probabilities. The mean of

[10] In general, we distinguish between two periods of the curriculum: the first year consisting of compulsory courses only, and the subsequent 2nd and 3rd year consisting of compulsory and elective courses.

the distribution is by construction centered at zero and peers contribution follows a fairly normal distribution. We do not observe any bunching at the top or bottom of the distribution. Rather, it appears that the majority of peers has only small impact on others' performance. In fact, 86 percent of peers have a peer value-added that is smaller than 5 percent of a standard deviation in performance. This suggests that *shining lights* and *bad apples*, students at the very top and bottom of the PVA, play an important role in producing peer effects –groups often not well captured by canonical peer effect models.

Table 3 summarizes the variation in peer value-added for all remaining outcomes. The value of a given PVA measure needs to be interpreted relative to the sample mean of zero. For example, a student with a peer-value added of .05 will, on average, increase the standardized grade of her peers by 5 percent more than the average peer observed in the data. Column (1) shows number of students for which we estimated individual peer value-added. Column (2) shows the across peer standard variation in PVA and Columns (3)-(7), shows various percentiles of the PVA distribution. Column (8) shows the p-value of a test of joint significance of peer fixed effects for the respective outcome.

Table 3 shows that value-added differs significantly between peers and that peers have a meaningful impact on both contemporaneous and subsequent performance. Meeting one peer in one course who has a one standard deviation higher PVA increases current grades by 3.3 percent of a standard deviation. Meeting a peer with a one standard deviation higher PVA in average second and third grades increases these grades by 5.5 percent of a standard deviation. Due to different standard deviations of non-standardized first-year grades compared to average 2^{nd} and 3^{rd} year grades, these effects are almost identical in absolute terms. The variation in PVA for graduation probabilities is similar to the PVA in current grades. Meeting a peer with a one standard deviation higher graduation PVA increases own graduation probability by 2.8 percent, from a mean of 48 percent. The size of this effect is economically significant and shows that peers have a powerful impact on students' study success.

We also observe significant peer value-added in self-reported outcomes based on student course evaluations. A standard deviation in peer value-added in self-reported study effort is equal to.76 study hours – or 46 minutes per week. Peer value-added in standardized perceived peer quality is significant as well with a standard deviation of 12 percent. Across all objective and self-reported outcomes, F-tests of joint significance following a regression of outcomes on individual peer fixed effects (Column 8) reject the null hypothesis of irrelevance of peers.

Peer capital. While peer value-added quantifies the spill-over of a single peer, this measure does not tell us how much the overall peer composition matters for students study success. On average, a student meets about 55 distinct peers through the random section assignment during the first study year. These peers differ in their peer value-added. While some of them will be valuable peers and inspire higher performance, compared to the average peer, others will harm student performance. To quantify how much all peers a student meets during their first study year affect performance we introduce the concept of peer capital: Inspired by the concept of social capital (Putman 1995) we can describe the PVA of all peers students are exposed to in their first year, as the "peer capital" of a student.

Figure 2 and 3 show the distributions of peer capital for the outcomes grades and graduation. Both figures highlight how important the interactions with a random set of peers are for an educational trajectory. The "lucky" 25 percent of students who met the most valuable peers have an 8 percent of a standard deviation higher end of first-year GPA compared to the 25% of “unlucky” of students who met fewer valuable peers. With respect to graduation, the lowest quartile of the peer capital distribution has a 6.8 percentage point lower probability to graduate than the highest quartile of peer capital. These results show that peer capital – the overall value-added of all peers – is a valuable asset for educational success.

Correlates of peer value-added. We next analyze which observable peer characteristics correlate with PVA. While we argue in Section 2 that peer value-added captures role model behavior, skill complementarities set or gentle personalities – we cannot directly observable these in our data. We do observe, however, a number of peer characteristics, namely gender, nationality and the pre-assignment university GPA. We next analyze whether these observable peer characteristics relate to a higher PVA. Table 4 shows how pre-treatment GPA, gender and nationality relate to the various PVA measures we constructed. Columns (1)-(3) show that the peer value-added measures for grades, subsequent average grades and graduation are only very weakly correlated with students’ pre-treatment GPA. They do not vary with gender or nationality. In all columns the F-test for joint significance rejects that student characteristics are jointly significant.[11] This lack of correlation is especially noteworthy for pre-determined GPA as shown in Figure 4. Apparently, it is not the high-performers who bring out high performance in others – an implicit assumption of most models of ability peer effects. Instead, the value-added of a peer seems to be almost orthogonal to own performance. However, as the data contains only a few observable student characteristics, we cannot rule out that PVA is systematically related to other, in our data unobservable, characteristics. It is also important to note that our measure of achievement – pre-

[11] While linear partial correlations between observables might mask non-linear relationships the bin-scatter in Figure A3 does not suggest the existence of such non-linearities. The bin scatter shows an unsystematic and insignificant relationship between own GPA and PVA.

determined GPA – is based on only a handful of grades. As students just entered university this GPA might be too noisy accurately measure ability.

Correlation in peer value-added across different outcomes. Do peers that raise performance also increase graduation chances of fellow students? And do student notice valuable peers when they are asked to evaluate the group functioning? We try to shed light on these questions by studying how much peer value-added is correlated across outcomes. The degree to which PVA overlaps for different outcomes is informative about how outcome or context specific peer value-added measures are.

Table 5 shows pairwise correlations between peer value-added for different outcomes. All PVA measures for objective educational outcomes are positively correlated with each other. Students who increase peer performance in the first year, also have a positive influence on later second and third grades. For example, a peer, which raises a students' first year grades by 10 percent of a standard deviation also raises that students' later second and third year grades by on average 1.8 percent of a standard deviation. This correlation between contemporaneous and future effects suggest that the contemporaneous impact of first year peer persists at least to some degree into later periods. We also find a positive correlation PVA in first year grades and graduation probabilities. On average a 10 percent increase in PVA in first year grades is related to .84 percent increase in graduation chances – a small yet statistically significant effect. Perhaps not surprising we also find that peers who raises subsequent performance on average also raise graduation probabilities.

PVA measures based on objective and subjective outcomes are also correlated, though to a lesser degree. Peers who raise individual performance by 10 percent standard deviation raise students' perceptions about the quality of peer-to-peer interactions on average by .27 percent of a standard deviation. This finding is interesting as it suggest that our peer-value-added measures are picking something up that student also perceive in the classroom and that affects the way they evaluate the peer-to-peer interaction in the student course evaluations. Notably, PVA in contemporary performance is negatively correlated to PVA in study hours. Those students who raise their fellow section mates' performance also seem to decreasing their average effort provision. While self-reported study hours are obviously a noisy measure of true study efforts, this negative relationship points to substitution effect of peer-supported and own learning. Students who meet peers with higher PVA appear to substitute their own study efforts with their peers' ability of teaching them the course material. Alternatively, spending time with high value-added peers may increases the efficiency of self-studying.[12]

5.2 Validating Peer Value-Added

After describing the variation in peer value-added in our setting we now investigate the stability of PVA over time and across subjects. We then validate PVA by testing its out-of-sample predictive power for spillovers among newly assigned peers and examine what drives systematic changes in PVA over time.

Stability of peer value-added. In the conceptual framework in Section 2, we described PVA to consist of a fixed, non-context-specific component as well as a transitory component that might

[12] Figure 5 shows four binned scatter plot on the relationship between various peer value-added measures. The Figure does not suggest that any of these relationships masks important non-linearities.

change with contextual factors. To assess the extent of this transitory component, we next investigate how stable PVA is over time and subjects.

How much does peer value-added change over time? Figure 5 shows how PVA estimated based on first year interactions is correlated with PVA estimated based on second and third year interactions. Both PVA measures were estimated on separate distinct samples that do not overlap. Figure 5 shows that PVA measures from both periods are significantly correlated with a partial correlation of $\beta = 0.08$. This fairly low correlation hints at a strong transitory component in PVA which is stronger than what is typically found in the teacher value-added literature. This lower over-time stability, however, is not entirely surprising considering that students take different type of courses, learn new content, meet new teachers and interact with new peer groups. Noteworthy, the beginning of university studies is a formative period for many students – a period which could also systematically alter how much others can learn from them. For teachers, in comparisons to peers, most of these aspects do not change this dramatically from one year to the next.

We further assess the stability of PVA across courses of different subjects. To do so, we separately estimate PVA based on math-intensive and non-math-intensive courses and test how much these are correlated. The lower panel of Figure 6 shows the relationship between PVA in mathematical versus non-mathematical courses, with the regression coefficient shown as a regression line. The correlation coefficient is $\beta = 0.074$ and comparable to the year-to-year correlation. We conclude from this that PVA in different subjects is related, though imperfectly. On average, a student who raises his peers' performance in math-intensive subjects also tends to increase his fellow students' performance in non-math-intensive courses.

Predictive power for future interactions. For peer value-added to serve as a useful tool in designing peer assignment mechanisms, PVA should be able to predict a peers' value-added in a sample separate from the one where it was estimated in. To evaluate this feature of PVA, we exploit the fact that, in all new courses students take after the first year, they are again randomly allocated to peer groups. We then test if PVA measured based on 1st year courses is predictive for outcomes of newly assigned peers in second and third year. To do so, we regress individual standardized course grades obtained in second and third year on peers' value-added. As these grades are obtained among newly assigned peers – different from those the PVA is based on – we thus test the *out-of-sample* predictive power of PVA. The upper panel of Figure 7 visualizes the regression results of this exercise. The results show that PVA measured in the first year is indeed a predictor for newly assigned peers' performance in later years. A one standard deviation increase in PVA based on first year courses raises performance in newly assigned peers by 0.12 percent of a standard deviation – about a tenth of the effect in contemporary 1st year interactions. The size of this effect corresponds closely to the degree of over-time and across-subject reliability of PVA found at the peer level in the previous section.

Taken together, we conclude from these results that PVA is predictive for outcomes of newly assigned peers in later periods – outside of the context where it was estimated in.[13] Showing that PVA has predictive power to later outcomes addresses one of the shortcomings in the peer effects literature, which has criticized itself for not being able to deliver valid out-of-sample forecasts of spillovers based on observable student characteristics (Carrell, Sacerdote and West, 2013).

[13] We cannot provide a causal estimate on the relationship between own PVA and own earnings, as PVA might be correlated with further unobservable factors on the individual level and we cannot rely on any quasi-experimental variation in PVA. We nonetheless regress own earnings on PVA to examine the correlation between both variables. PVA is not significantly correlated with PVA.

Systematic changes in peer value-added over time. Peer value-added displays a rather low correlation over time and appears to consist of a sizeable transitory component. So, why does peer value-added change so much from one year to the next? To bring some evidence on this matter we take advantage of the repeated exogenous exposure to different peer groups and examine to which degree we can explain changes in PVA by exposure to differing peer environments in previous periods. Put differently, we ask, do the peers students meet during the first year affect their subsequent PVA.

To test the idea that peers influence own PVA we regress individual peer value-added constructed on second and third year courses on peer capital – the overall PVA of all the peers students met in their first year. Table 7 show how exposure to high peer-value added peers affects student own PVA in the next period. For both measures of peer capital, estimates show that a peers' own PVA changes systematically after exposure to higher value-added peers in earlier periods. A one standard deviation increase in students peer capital raises their own subsequent PVA in grades by 4.3 percent of a standard deviation.[14]

While this malleability of peer-value added is striking, we can only speculate on the sources behind this systematic change. On the one hand, students might adapt peer behavior they observed and benefited from in earlier periods. They may ask more informative questions, i.e. fewer questions about how to cluster standard errors, display more supportive behavior during class, or help to better prepare their peers for the examination. Whatever is driving these systematic changes in PVA, these 'learning effects' imply that students who meet high value-added peers do not only

[14] Figure 8 shows that this simple linear effect is a decent approximation of the overall effect and does not hide strong non-linearities.

perform better themselves, but subsequently also produce larger spillovers themselves – they become better at teaching to other students. Noteworthy, this effect is in line with similar results from the teacher effectiveness literature. Jackson and Bruegmann (2009) show that teacher's effectiveness increases in after exposure to more high-value added colleagues.

5.3 Heterogeneity of PVA in Student-Peer Match Characteristics

The peer value-added measures we use in the paper identify the average effect that a peer as on outcomes of other students. Obviously, the impact of a peer is unlikely to be fully homogenous across all social interactions. Some students may be better at helping academically weak student, while others' may have a bigger impact on students of the same gender. While potential heterogeneity of value-added in the match characteristics of student-peer interactions does not impede the identification of average peer value-added estimates it remains interesting to investigate if peer value-added is universal or match-specific. Knowledge about such heterogeneities in PVA is vital for future advice on how to re-assign peers to increase overall performance.

In order to understand how general peer-value added is, we follow the out-of-sample prediction approach used in the previous section. We regress individual grades obtained in second and third year on PVA and the interaction between PVA and match characteristics. As match characteristics, we consider whether peer and student have the same gender, same nationality, or similar past achievement. Table 8 shows the estimation results on how pre-treatment PVA interacts with student-peer match characteristics. Table 8 shows that the main effect of PVA is largely independent of whether the student and peer match in terms of gender, nationality or GPA. Matching characteristics, though, have a positive effect in themselves. Students appear to benefit from meeting more individuals of same gender and nationality. These type of peer effects reflect what type effects that canonical peer effects model can identify. These positive effects of meeting students similar to oneself, however does not interact with the spill-over of individual peers.

6. Discussion

6.1 Relationship to Prior Work – Peer Effects and Teacher Value-Added

Based on randomized repeated assignments of students to sections in a business school, we have identified the peer value-added as the ability of a single peer to raise others' performance. While we find meaningful variation in PVA in the student population, it appears not to be systematically related to peer observable characteristics. Most noteworthy, PVA turns out to be orthogonal to own past achievement in our setting. This could in part be due to the fact that our measure of past achievement – university GPA – is constructed only on a handful of previous grades and therefore represents a noisy measure.

We estimate peer-specific value-added by drawing from the literature on teacher effectiveness (Chetty et al. 2014, Hanushek and Rivkin 2006, Jacob and Lefgren 2005, Kane and Staiger 2008). How do our peer value-added do measures relate to the results in this literature? Figure 9 compares our peer value-added estimates to the ones found in the literature on teachers and school principals. The variation in peer value-added is significantly smaller than the variation estimated for teacher- or principal value-added. The median variation in teacher-value added is .11 of a standard deviation in student performance. With .033 our estimate of peer value-added is about one third of size of these median estimates.

Similar to the teacher literature, peer observables are bad predictors for peer value-added. We further show that exposure to high PVA peers increases own subsequent value-added among newly assigned peers. Jackson & Bruegmann (2009) document similar learning spillovers among teachers value-added.

We find that PVA is systematically correlated over time and context and is predictive for peers' outcomes *out-of-sample*. Changes in PVA can be partially explained by interactions with high PVA peers in earlier periods. Finally, PVA does not interact with characteristics of specific student-peer matches.

Our findings have a number of implications for how to interpret existing findings from the literature on peer spillovers. First, the large variation in PVA implies that peer effects studies applying restrictive functional form might not capture the role of "shining lights" and "bad apples" for peer spillovers. For example, focusing on average peer group characteristics is likely to oversee peer influences if peer effects can be attributed to a few high PVA students. We think that the surprisingly small magnitude or entire lack of peer spillovers found in many settings might be misleading regarding the existence and size of peer spillovers.

Second, the lack of correlation between PVA and observable characteristics in our setting could imply that canonical peer effect studies on achievement, gender, or ethnicity do not necessarily capture the relevant dimensions in which students affect their peers. Estimates of peer effects in single observable dimensions might not be informative about the lack or presence of peer effects in general when the ability to raise others' performance is orthogonal to observables. We believe that absence of peer effects in peers' average observable characteristics does not necessarily imply absence of peer effects in general.

Third, our findings show that the skill of bringing out the best in other is something that can be altered and learned from interacting with valuable peers. The fact that changes in PVA can be to some degree be explained by exposure to high PVA peers in earlier periods suggest that there is potential for interventions that try to make students “better peers”.

With our paper, we complement the approach by Arcidiacono et al. (2017) who estimate individual-specific peer spillovers. Arcidiacono et al. (2017) use possession-player level data from the National Basketball Association to estimate player-level contributions to others’ performance.[15] Lacking information on individual player productivity their estimations rely on structural estimations using a multinomial logit type production technology. In contrast to our approach Arcidiacono et al. (2017) cannot reshape their dataset, since by definition of a possession, only one player, if anyone, can score per possession. Compared to this study, we rely on random assignment of students to peers and use individual-specific and contemporaneous performance measures. In addition, our setting of small peer groups engaging in cognitive skill-intensive environment perhaps has larger external validity, speaking to many workplace and educational production settings.

6.2 Applications in Education Policy and Human Resources Management

Going beyond this paper we see potential to apply the methods developed in this work in settings that include merit- or performance-based evaluation, incentives, or performance feedback. In many education and workplace settings agents are awarded for their individual output – but not how much they contribute to the performance of others. When peer spillovers are substantial, individual-specific performance measures will insufficiently describe one’s actual contribution to team

[15] A possession in basketball is defined as the period from when a team takes the offensive until it scores, loses the ball, or commits a violation or foul.

production. Incentives for individuals may even discourage helping peers to do well and decrease overall productivity. The measures of peer value-added proposed in the paper could be used to reveal valuable coworkers and to quantify their contribution to others output. Peer value-added could potentially also be used to adjust individual productivity measures for contributions that should be attributed to specific co-workers. We believe that knowledge of peer value-added, the individual-specific spillover, could be the key to allocating individuals to output maximizing teams.

Taken together our findings also raise an interesting question with respect to complementarities among workers in the workplace: Do firms pay workers with a higher peer value-added higher wages? Firms who overlook productivity spillovers and only pay their employees based on their own productivity may dis-incentivize workers and behavior that brings out the best in others.

7. Conclusion

This paper introduced a new way to quantify the importance of peers. Building upon methods developed in the teacher effectiveness literature we describe a concept to isolate the value-added of an individual peer to others' performance – the peer value-added. Peer value-added summarizes observable and unobservable spill-over on others' performance that could be driven supportive or disruptive behavior, degrees of complementary in skill sets, or differences in non-cognitive skills that contribute to a productive learning environment.

We estimate peer value-added in a sample of Economics and Business students who are repeatedly and randomly allocated to teaching sections within a Dutch business school. This application reveals significant variation in how much peers affect performance. In our setting, the majority of peers has only a small impact on performance: Out of all peers that students interact with, only 14 percent affect grades by more than 5 percent of standard deviation. Peer value-added appears to be largely unrelated to peers' observable characteristics, most notably it is only very weakly correlated with own past achievement. Within students, peer value-added is correlated across outcomes, time and subjects. Further, peer value-added is a valid predictor for newly assigned peers in later periods. Strikingly, changes in peer value-added can be partly explained by previous exposure to high value-added peers itself. It thus seems students' peer capital is productive, and that students learn 'how to be a good peer' from interacting with peers who are good at bringing out the best in others.

The conceptual framework we introduce and the estimation we propose in this paper has potential to compare variation in peer value-added across contexts and environments in future research. The method proposed in this paper can be applied in settings with repeated performance observation and variation in group composition. Peer value-added may therefore serve as a tool to re-assess the importance of peers in a variety of education and workplace settings where peer effects have previously been documented.

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TABLES AND FIGURES

Tables

Table 1: Descriptive Statistics

	(1) N	(2) Mean	(3) Sd	(4) Min	(5) Max
A. Student Demographic Characteristics					
Female	4,729	0.369	0.482	0	1
Dutch	4,729	0.292	0.455	0	1
German	4,729	0.449	0.497	0	1
Age	4,729	19.13	1.450	16.19	31.21
B. Student Performance					
Pre-assignment GPA	26,319	6.681	1.467	1	10
Course grade in year 1	23,784	6.228	1.774	1	10
Std. average grade in year 2 & 3	19,993	-0.008	1.045	-5.148	2.572
Graduation	15,760	0.634	0.482	0	1
C. Students Course Evaluations					
Self-reported study hours	8,580	12.00	7.846	0	70
Std. subjective peer quality	8,128	-0.102	0.982	-3.741	1.641
Std. subjective instructor quality	8,139	-0.093	1.097	-3.617	1.385

D. Summary Statistics of Dyadic Student-Peer Interactions	N (1)
Number of students	4,729
Number of peers	4,729
Number of sections (peer groups)	2,567
Number of course-year observations	176
Number of bilateral student-peer interactions within sections	289,919
Average number of student per section	13.77
Average number of dyadic interactions per group	175.87
Average number of student-peer interactions conditional on meeting once	1.21

NOTE.— This table shows the descriptive statistics of estimation sample. 'Sd' refers to the standard deviation of the respective variable. Panel A reports individual student characteristics. Panels B and C report outcomes at the student-course level. Smaller numbers of observations in Panel B are due to students drop out. Smaller numbers of observations in Panel C are due to response rates to teaching evaluations. Panel D shows the descriptive statistics of estimation sample before and after reshaping to dyadic student-to-student interaction data.

Table 2: Test for Random Assignment of Students to Sections

Dependent Variable	Number Significant at the:			Percent Significant at the:			Total Number of Courses	Mean of p-value
	5%	1%	0.1%	5%	1%	0.1%		
Female	6	0	0	3%	0%	0%	172	0.5250
GPA	8	2	0	5%	1%	0%	153	0.4685
Age	8	4	0	5%	2%	0%	175	0.5044
ID Rank	6	0	0	3%	0%	0%	175	0.5133

NOTE.—This table is based on separate OLS regressions with gender, GPA, age and ID rank as dependent variables. The explanatory variables are a set of section dummies and dummies for the other parallel course taken at the same time and the nationality indicators German and Dutch. Columns (2) and (3) show in how many regressions the F-test on joint significance of all included section dummies is statistically significant at the 5 percent and 1 percent level, respectively. Columns (5) and (6) show for what percentage of the regressions the F-test rejected the null hypothesis at the respective levels. Differences in number of courses reported in Column (1) are due to missing observations for some of the dependent variables. We do not include German and Dutch as dependent variables since these variables are mechanically balanced due to the stratification of assignment by nationality. For more detailed explanation of this randomization check see Feld and Zölitz (2017).

Table 3: Summary Statistics of Peer Value-Added Estimates

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
			Percentiles					p-value F-Test of joined sig. of peer FE
Peer Value-Added Estimate	N	SD	p1	p5	p50	p95	p99	
Performance indicators								
Std. course grade 1st year	4,604	0.0333	-0.0921	-0.0588	0.0003	0.0583	0.0923	0.0160
Std. average course grade 2nd & 3rd year	4,285	0.0552	-0.1356	-0.0845	0.0012	0.1058	0.1476	<0.001
Graduation	3,214	0.0279	-0.0781	-0.0492	0.0002	0.0485	0.0708	0.0380
Self-reported measures								
Self-study hours	4,380	0.7648	-2.2137	-1.5518	-0.0353	1.0414	1.7652	<0.001
Subjective peer quality	4,345	0.1243	-0.3169	-0.1922	0.0039	0.2483	0.3517	<0.001

Note: This table reports summary statistics of value-added estimates at the peer level. Grades are standardized to mean zero and unit variance. Self-study hours are in their natural unit. Subjective peer, instructor and learning material quality represent indexes based on multiple questions which are standardized to mean zero and unit variance. The number of observations differs by VA measures due to missing values of outcomes. Column (8) reports the p-value of a joint significance test of the peer fixed effects as predictors of each outcomes. F-Tests are based on regular standard errors.

Table 4: Who Makes a Good Peer?

Correlation between Student Characteristics and Various Peer Value-Added Measures

	(1)	(2)	(3)	(4)	(5)
Dependent Variable: Peer Value-Added in...	Std. course grade	Std. average 2nd and 3rd year grade	Graduation	Self-study hours	Subjective peer quality
GPA	0.0005*	-0.0004	-0.0002	0.0013	0.0019*
	(0.000)	(0.001)	(0.000)	(0.007)	(0.001)
Female	0.0001	0.0023	0.0002	0.0007	0.0008
	(0.001)	(0.002)	(0.001)	(0.022)	(0.003)
German	-0.0012	0.0024	0.0005	0.0505*	-0.0017
	(0.001)	(0.002)	(0.001)	(0.028)	(0.004)
Dutch	-0.0005	0.0033	0.0008	0.0382	-0.0001
	(0.001)	(0.002)	(0.001)	(0.030)	(0.005)
Observations	4,582	4,262	3,192	4,361	4,324
R-squared	0.001	0.001	0.000	0.001	0.001
p-value of F-Test for joint significance of student characteristics	.4436	.3602	.8898	.4901	.4894

Note: This table reports results of regressions of PVA in different outcomes on peer observable characteristics. One observation per student. Robust standard errors are in parentheses. Significance levels indicated as * p<0.1, ** p<0.05, *** p<0.01.

Table 5: Correlation Between Peer Value-added Measures of Different Outcomes

Pairwise Correlation between Peer Value-Added Measures	(1) Contemporaneous Course Grade	(2) Average 2nd and 3rd Year Grade	(3) Graduation	(4) Self-study Hours
Average 2nd and 3rd Year Grade	0.1811***			
Graduation	0.0840***	0.2186***		
Self-study Hours	-0.0308**	0.0030	0.0137	
Subjective Peer Quality	0.0274*	0.0314**	-0.0171	0.0781***

Note: This table reports results from pairwise regressions of PVA in different outcomes on the level of individual peers. Self-study hours are measured from self-reported student course evaluation data. One observation per student. Robust standard errors are in parentheses. Significance levels indicated as * p<0.1, ** p<0.05, *** p<0.01.

Table 6: Validation of Peer Value-Added – Predictive Power of PVA for New Interactions

Dependent Variable: Std. Course Grade in 2nd/3rd Courses	(1) Std. Course Grade	(2) Std. Course Grade	(3) Std. Course Grade	(4) Std. Course Grade	(5) Std. Course Grade	(6) Std. Course Grade
Peer Value-Added for 1st year grade	0.1200***					0.1234**
	(0.040)					(0.048)
Peer Value-Added for future 2nd/3rd year grades		-0.0148				-0.0195
		(0.023)				(0.028)
Peer Value-Added for Graduation			-0.0038			-0.0046
			(0.049)			(0.054)
Peer Value-Added for self-study hours				0.0002		0.0011
				(0.002)		(0.002)
Peer Value-Added for subjective peer quality					0.0220**	0.0164
					(0.011)	(0.014)
Observations	316,382	315,922	278,572	313,507	313,427	259,010
R-squared	0.449	0.449	0.442	0.449	0.448	0.442

Note: This table reports results from regressions of standardized course grade in second and third year on peer-value added measures constructed based on student-peer interactions in the first year of study. The estimation sample contains all student-peer interactions in second and third year courses. One observation per student-peer interaction. Robust standard errors using two-way clustering at the individual and section level are in parentheses. Significance levels indicated as * p<0.1, ** p<0.05, *** p<0.01.

Table 7: Is Peer Value-Added Malleable over Time? – Peers Influence on Own PVA

	(1)	(1)
Dependent Variable:	Std. Peer Value-Added 2nd/3rd year	Std. Peer Value-Added 2nd/3rd year
Std. Mean Peer Capital	0.0429**	
	(0.021)	
Std. Sum of Peer Capital		0.0449***
		(0.017)
Observations	2,930	2,907
R-squared	0.003	0.004

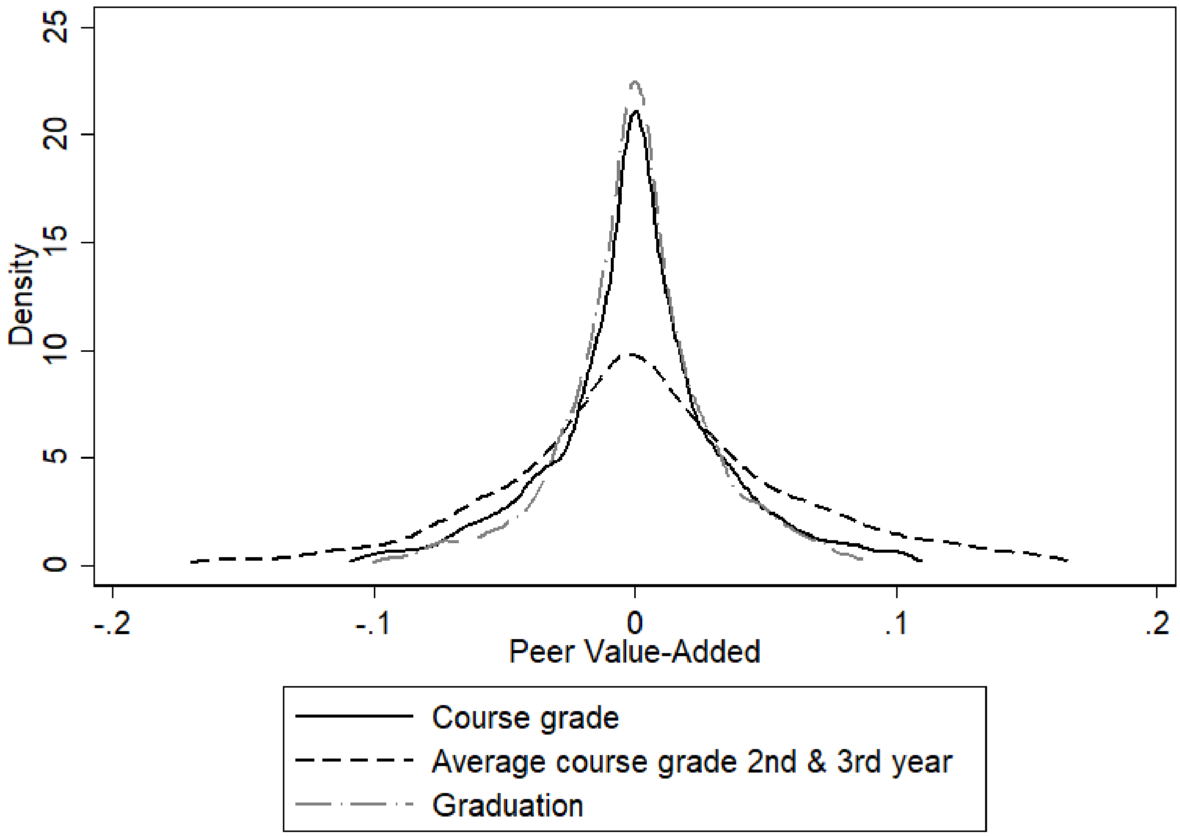
Note: This table reports results from regressions of peer value-added based on second and third year social interactions on the mean and sum of PVA of all peers met in the first year. One observation per student. Robust standard errors in parentheses. Significance levels indicated as * p<0.1, ** p<0.05, *** p<0.01.

Table 8: Does the Impact of Peer Value-Added Depend on the Student-Peer Match?

	(1) Std. Course Grade	(2) Std. Course Grade	(3) Std. Course Grade	(4) Std. Course Grade	(5) Std. Course Grade
Peer Value-Added	0.1200***	0.1540**	0.1197**	0.1059**	0.1126**
	(0.038)	(0.060)	(0.054)	(0.043)	(0.046)
Peer Value-Added * Same Gender Match		-0.0618			
		(0.095)			
Peer Value-Added * Same Nationality Match			0.0004		
			(0.097)		
Peer Value-Added * Same Gender & Nationality Match				0.0625	
				(0.112)	
Peer Value-Added * GPA Match					0.0287
					(0.081)
Same Gender Match		0.0054*			
		(0.003)			
Same Nationality Match			0.0117***		
			(0.004)		
Gender & Nationality Match				0.0084**	
				(0.004)	
GPA Match					0.0056
					(0.004)
Observations	316,382	316,382	316,382	316,382	316,382
R-squared	0.449	0.449	0.449	0.449	0.449

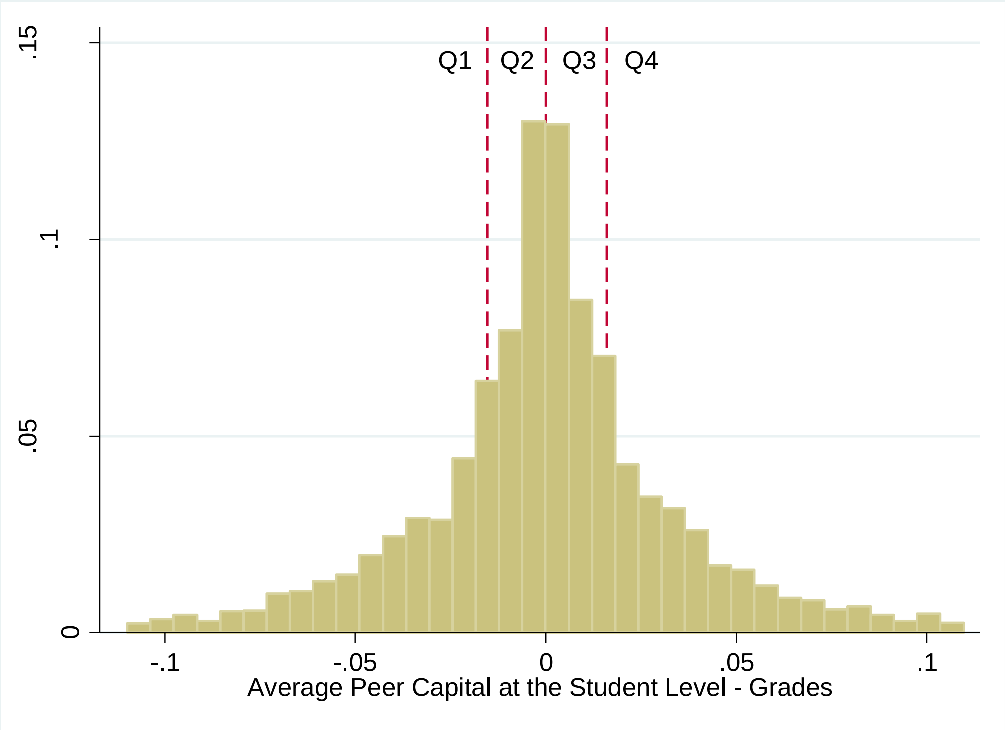
Note: This table reports results of regressions of students' grades in second and third year on PVA based on first year interactions and interactions with respective matches in observable characteristics between peer and student. One observation per student-peer interaction. GPA match is an indicator variable that equals one if the difference between student and peer GPA is less than 50 percent of a standard deviation. Robust standard errors using two-way clustering at the individual and section level are in parentheses. Significance levels indicated as * $p<0.1$, ** $p<0.05$, *** $p<0.01$.

Figure 1: Distribution of Peer-Value Added for Different Outcomes



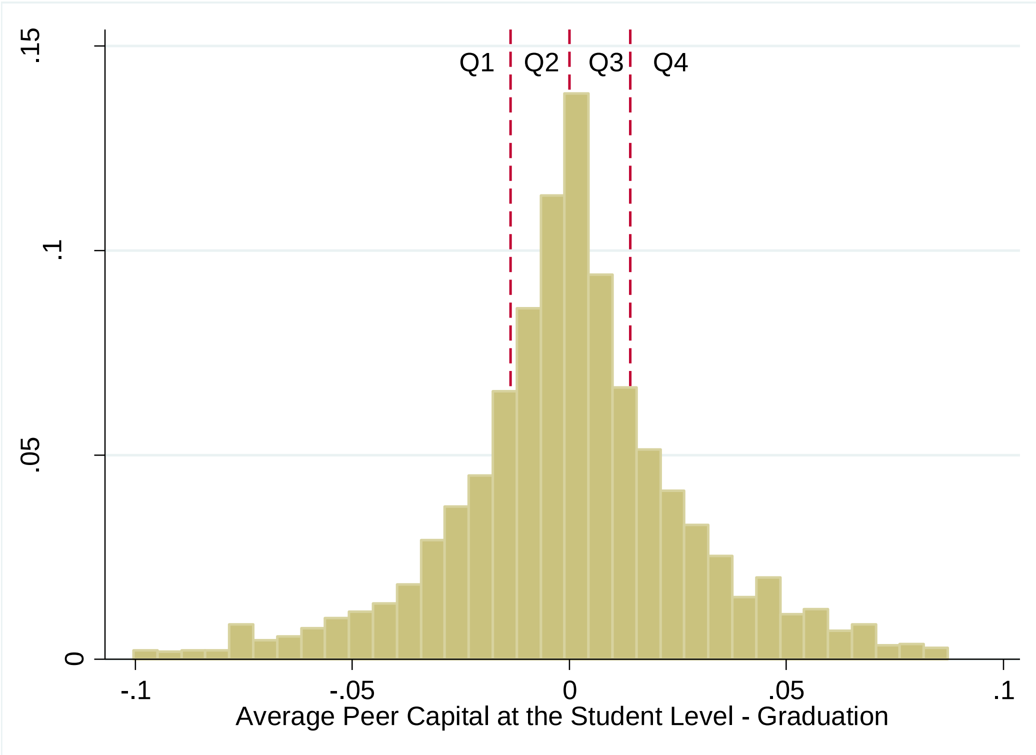
Note: This figure displays distributions of estimated peer value-added for three outcomes: (1) standardized course grade in the first year, (2) average course grade in second and third year, and (3) probability of graduation.

Figure 2: Peer Capital and End of First-Year Achievement



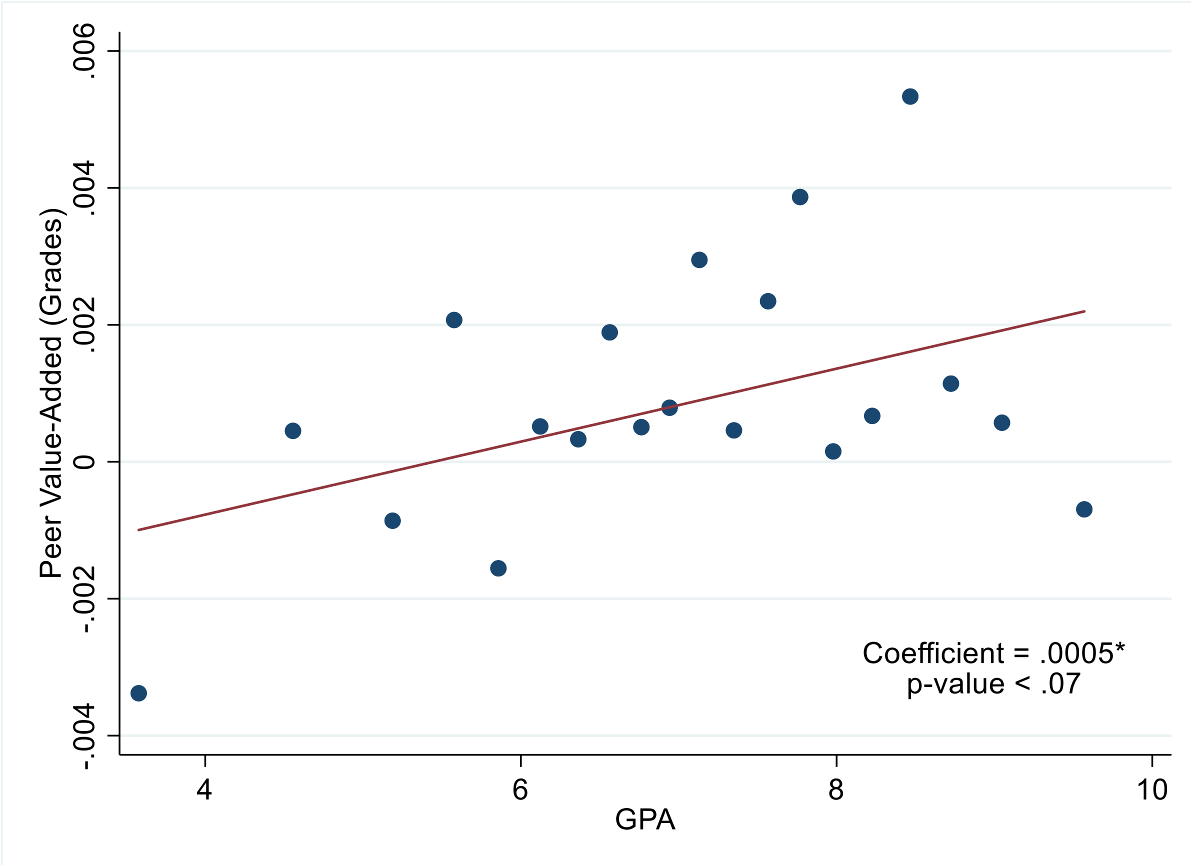
Note: This histogram visualizes the distribution of *peer capital* – the average peer value-added of peers met by a single student. The respective outcome is individual first year achievement. The vertical lines mark the 75th, 50th and 25th percentile of the peer capital distribution. The interquartile range is equal to .0675 percent. On average, students in the top quartile of the peer capital distribution perform 8 percent of a SD higher than students in the bottom quartile.

Figure 3: Peer Capital and Graduation Probabilities



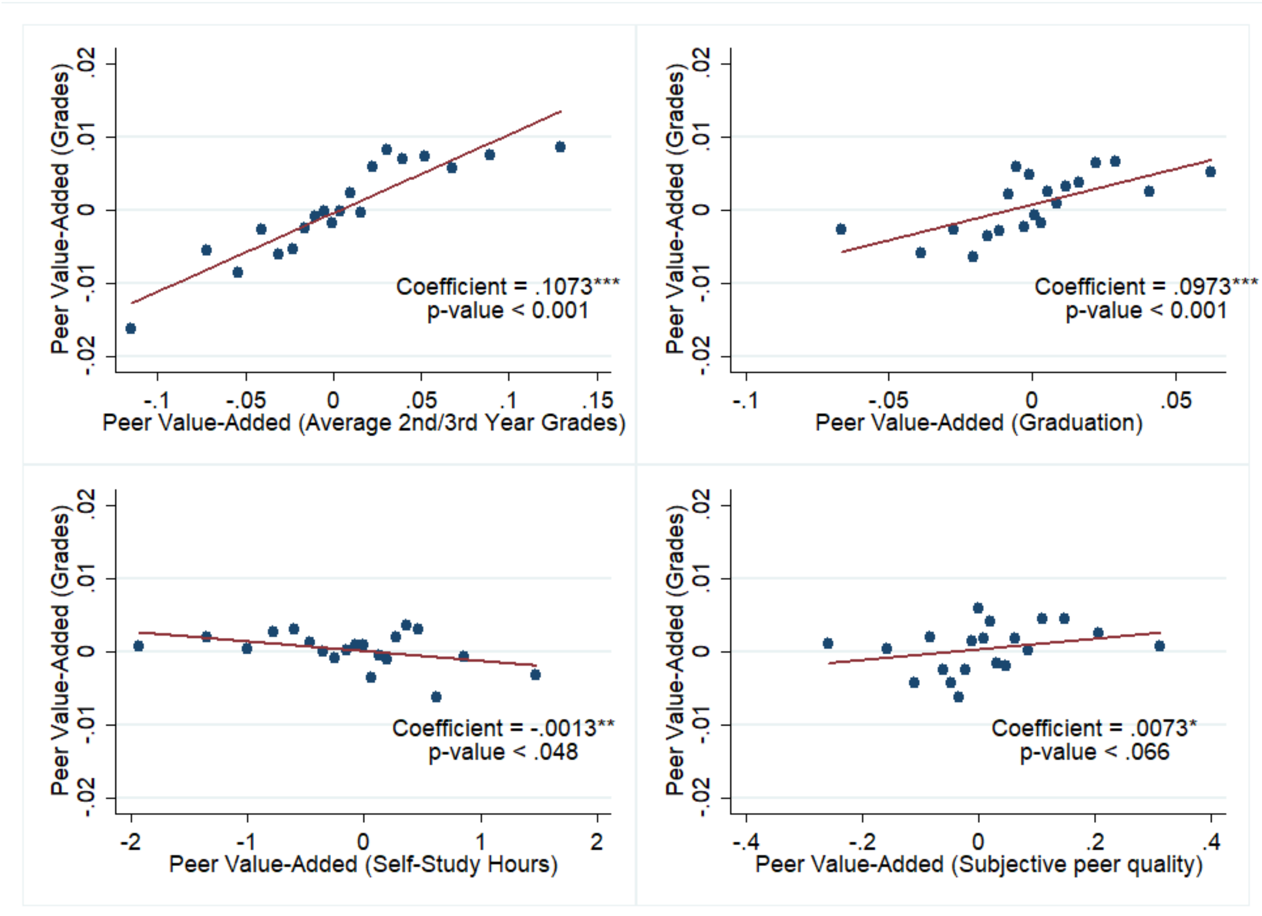
Note: This histogram visualizes the distribution of *peer capital* – the average of peer value-added of peers met by a single student. The respective outcome are individual graduation probabilities. The vertical lines mark the 75^{th}, 50^{th} and 25^{th} percentile of the peer capital distribution. The interquartile range is equal to .0675 percent. On average, students in the top quartile of the peer capital distribution are 6.8 percentage points more likely to graduate than students in the bottom quartile.

Figure 4: Correlation between Student GPA and Peer Value-Added



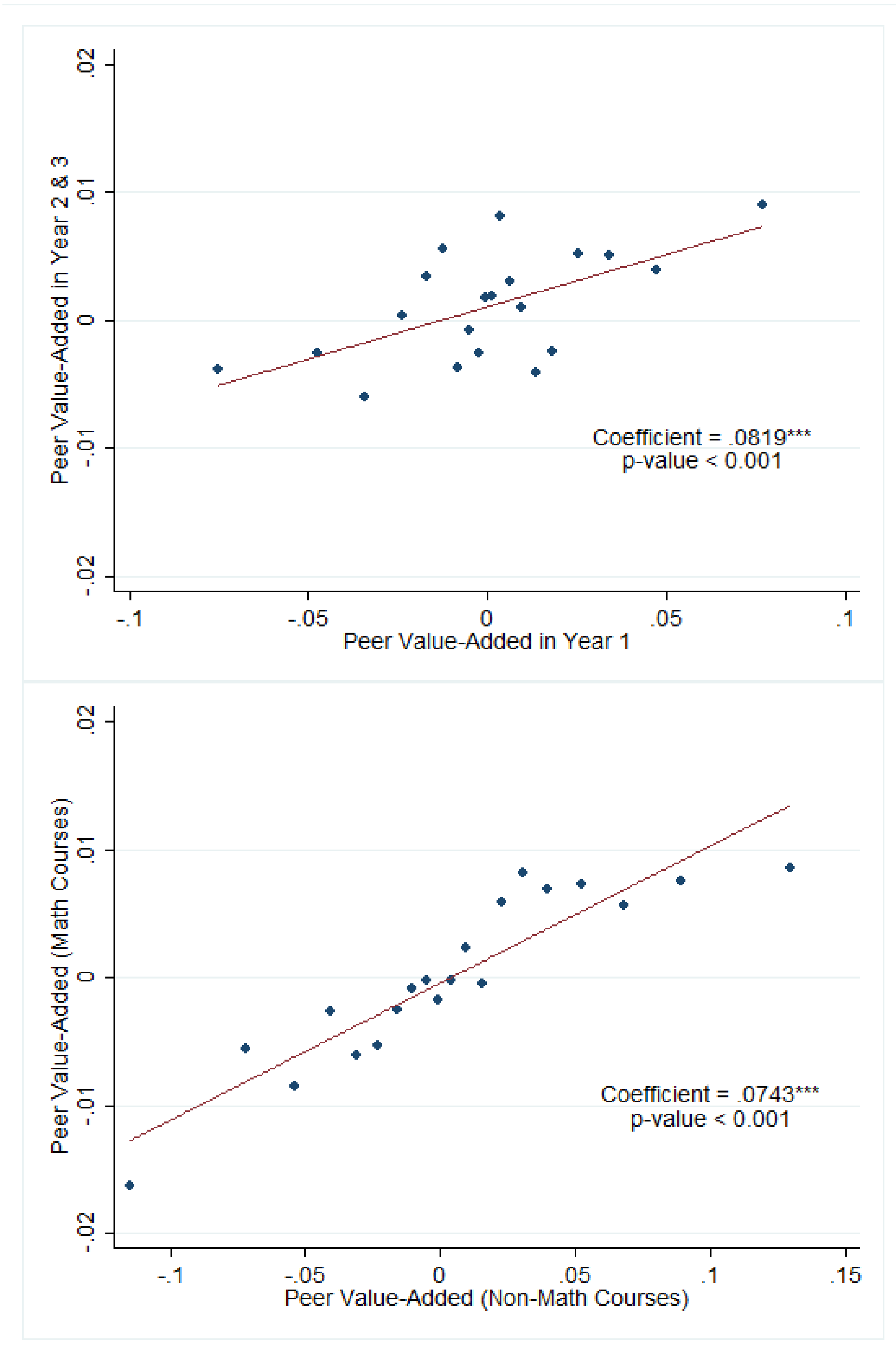
Note: These plots visualize the relationship between PVA and past GPA of a peer. The construction of the bin scatter follows Chetty et al. (2014b). The point estimate and significance level is obtained from a respective OLS regression (Table 4). N = 4,580. Significance levels indicated as * p<0.1, ** p<0.05, *** p<0.01.

Figure 5: Correlation between Peer Value-added in Grades and PVA in Other Outcomes



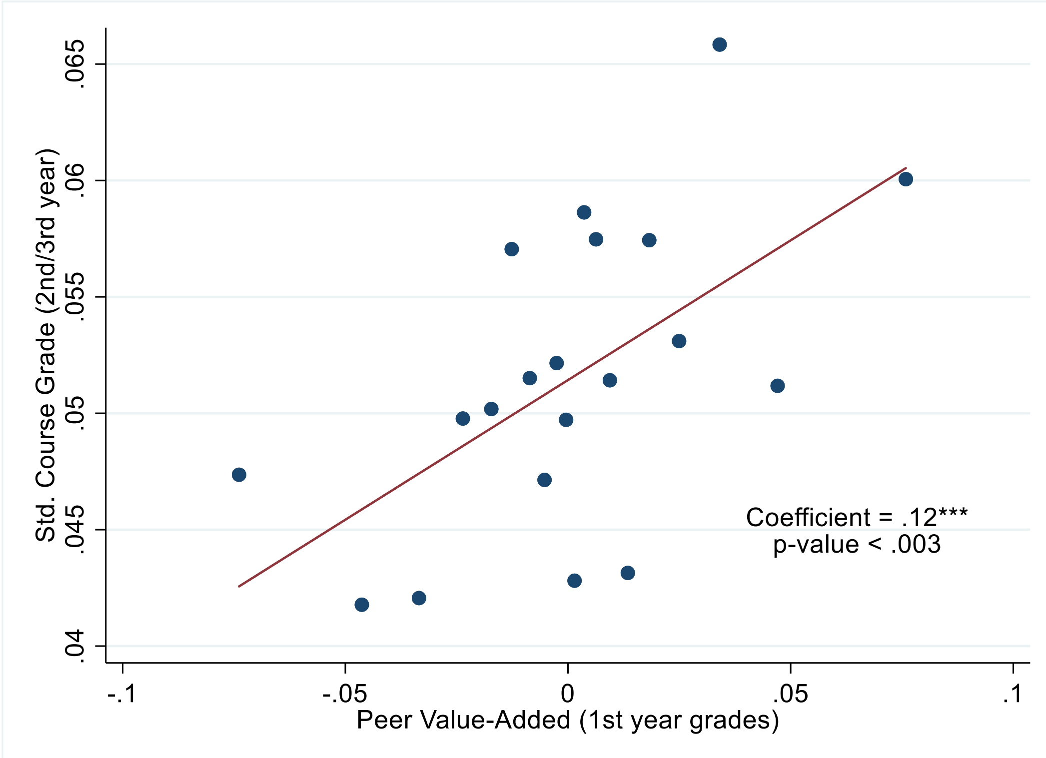
Note: These plots visualize pairwise relationships between PVA in grades and PVA for different outcomes. The construction of the bin scatter follows Chetty et al. (2014b). The point estimate and significance level is obtained from respective OLS regression (Table 5)s. Table 5 shows the regression table. N = 4,580. Significance levels indicated as * p<0.1, ** p<0.05, *** p<0.01.

Figure 6: Reliability of Peer Value-Added Measures across Time and Subjects
1st Year vs. 2nd/3rd Year || Mathematical vs. Non-Mathematical Courses



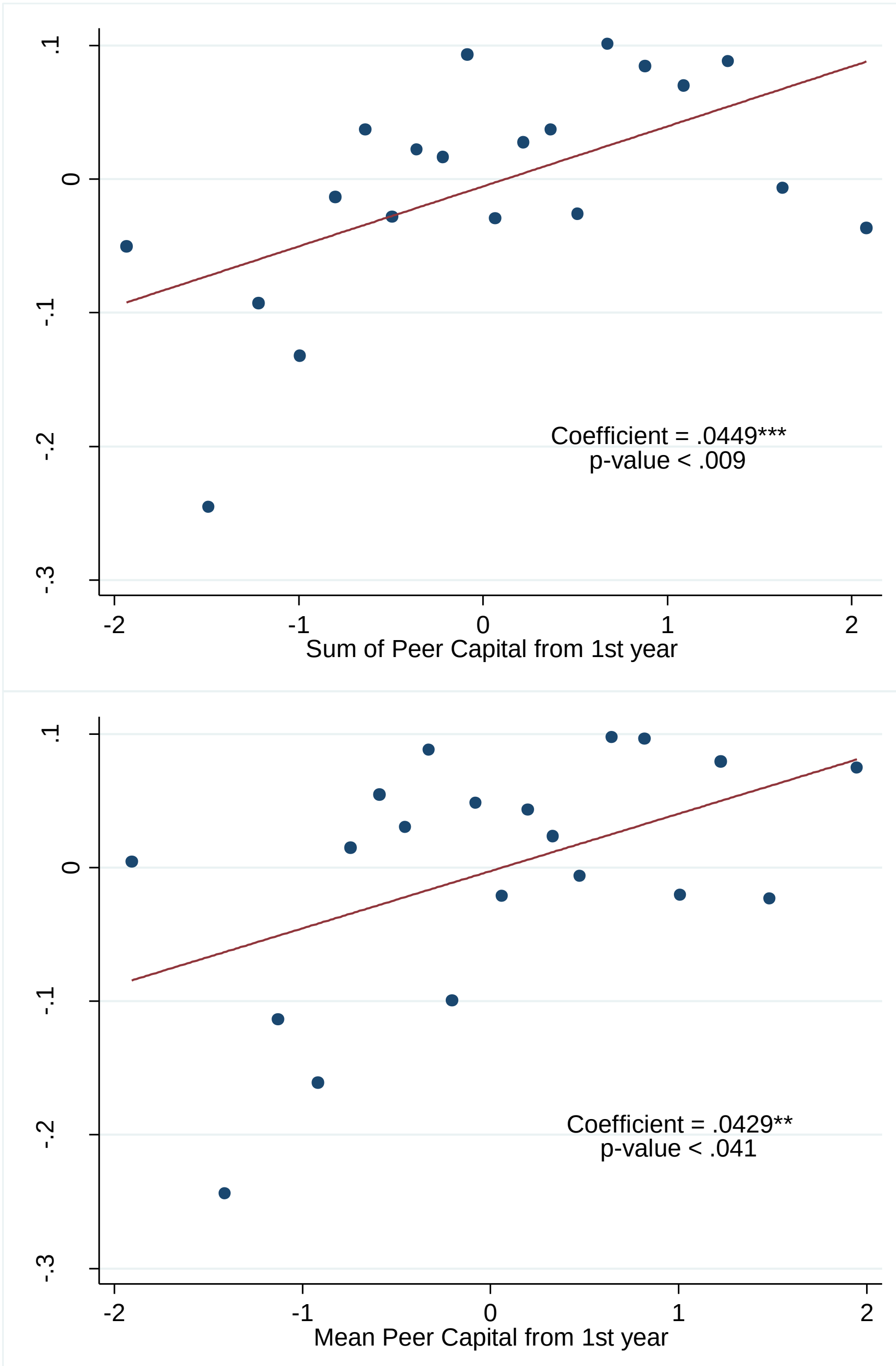
Note: These plots visualize the relationship between PVA estimated in separate periods (upper panel) and PVA estimated separately for math- and non-math intensive courses (lower panel). The construction of the bin scatter follows Chetty et al. (2014b). The point estimate and significance level is obtained from respective OLS regressions (Table 5).N = 4,580. Significance levels indicated as * p<0.1, ** p<0.05, *** p<0.01.

Figure 7: Out of Sample Prediction: Spillovers Arising from Pre-Sample Peer-Value Added



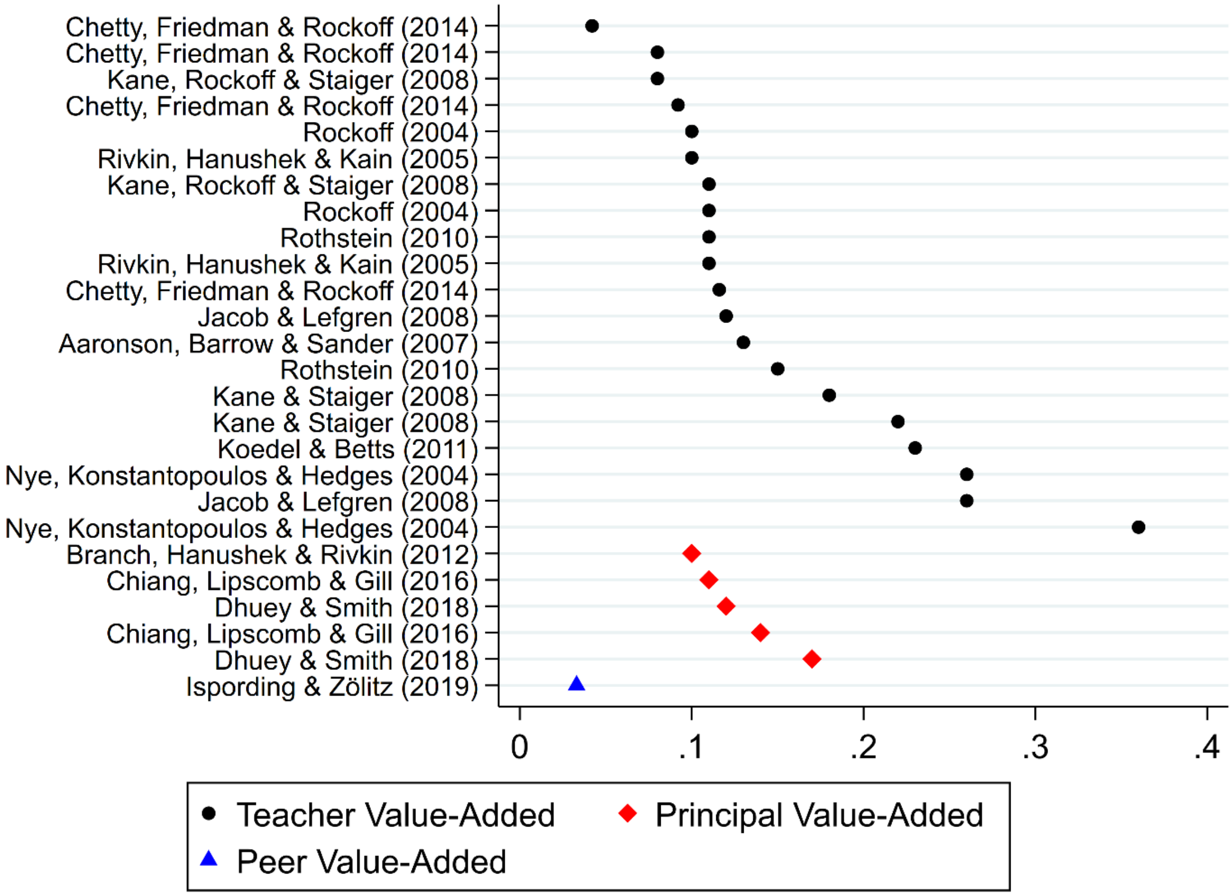
Note: These plots visualize the relationship between own grades in second and third year and the peer value-added of peers met in the first year. The construction of the bin scatter follows Chetty et al. (2014b). The point estimate and significance level is obtained from respective OLS regression (Table 6) The estimation sample consists on all student-peer interactions in second- and third-year courses. The peer-value added measures is constructed based on student-peer interactions and course grades in the first year of study. Top figure: N=316,382. Bottom figure: N= 93,991. Significance levels indicated as * p<0.1, ** p<0.05, *** p<0.01.

Figure 8: Impact of 'Peer Capital' – PVA of 1st Year Peers – on Own Peer Value-Added



Note: These plots visualize the relationship between own PVA in second and third year and the sum (upper panel) or mean (lower panel) of PVA of peers met in the first year. The construction of the bin scatter follows Chetty et al. (2014b). The point estimate and significance level is obtained from respective OLS regressions (Table 7). Peer value-added is constructed based on 2nd & 3rd year social interactions. The variables 'Mean Peer Capital' and 'Sum Peer Capital' are constructed based on a different pre-sample dataset of all first social interactions. 'Sum of Peer capital' is the sum the PVA measures of all peers a student met in their first year. One observation represents one student. N= 3,003. Significance levels indicated as * p<0.1, ** p<0.05, *** p<0.01.

Figure 9: Comparison of Teacher, Principal and Peer Value-Added



APPENDIX

Table A1: Data Structure before and after Reshaping

Panel A: Original data before reshaping

Student	Section
Julian	A
Dick	A
Anne	A
Anne	B
George	B
Timmy	B
No. of obs:	6

Panel B: Dyadic data after reshaping

Student	Peer	Section
Julian	Dick	A
Julian	**Anne**	A
Dick	Julian	A
Dick	**Anne**	A
Anne	Julian	A
Anne	Dick	A
Anne	George	B
Anne	Timmy	B
George	**Anne**	B
George	Timmy	B
Timmy	**Anne**	B
Timmy	George	B
No. of obs.		12

Note: In Panel A each observation represents one student-class observation. In Panel B each observation represents one student-peer match observation. The number of observations increases from $\sum_{c=1}^{C}\sum_{s=1}^{S} n_{cs}$ to $\sum_{c=1}^{C}\sum_{s=1}^{S} n_{cs}\,(n_{cs}-1)$ in the reshaped dyadic data.